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VIABILITY OF ADDITIVE MANUFACTURING FOR PRODUCTION AND TOOLING APPLICATIONS: A DEVELOPMENT OF THE BUSINESS CASE

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To the Graduate Council:

I am submitting herewith a thesis written by Christopher Charles Griffin entitled "VIABILITY OF ADDITIVE MANUFACTURING FOR PRODUCTION AND TOOLING APPLICATIONS: A DEVELOPMENT OF THE BUSINESS CASE." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Industrial Engineering.

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VIABILITY OF ADDITIVE MANUFACTURING FOR PRODUCTION AND TOOLING APPLICATIONS: A DEVELOPMENT OF THE BUSINESS CASE

A Thesis Presented for the
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ABSTRACT

As marketplace competition drives industrial innovation to increase product value and decrease production costs, emerging technologies foster a new era through Industry 4.0. One aspect of the movement, additive manufacturing, or 3D [three-dimensional] printing, contains potential to revolutionize traditional manufacturing techniques and approach to design. However, uncertainties within the processes and high investment costs deter corporations from implementing and developing the technology. While several industries are benefitting from additive manufacturing's current state, as the technology continues to progress, more companies will need to evaluate it for industrial viability and adoption. As such, there exists a need for a framework to evaluate the business case for investment review. While many papers in the literature provide cost estimation models for additively manufactured parts, there does not exist a thorough guide for decision making. This master's thesis report introduces a process to evaluate machine investment and part production between additive manufacturing and traditional manufacturing technologies using operational and financial key performance indicators. A case study application of the process yielded suspect part unit costs 3.71% higher than its literature basis, indicating a viable methodology. The present value total investment cost for an EOSINT M 270 machine tool, with a five-year lifespan, was determined to be $3,241,710 in the case context; breakeven point occurs beyond investment life at 2.28 years. Results were dependent on product valuation and assumptions made. Key output metrics indicated the suspect machine could generate 5,238 units annually at a 1.4 part per hour throughput rate. As part production was deemed feasible under the provided constraints, sensitivity analysis indicated material and equipment costs as cost drivers. Similarly, production drivers were found to be scan rate and machine utilization. Results were consistent with common belief that additive manufacturing is currently viable for small-to-mid series production, or parts of high complexity value. These findings indicate areas of improvement for the additive manufacturing industry for commercialization purposes, and demonstrate a useful methodology for assessing the business case of additive manufacturing.

PREFACE

This study was conducted in accordance with the requirements for completion of a Master of Science degree in Industrial Engineering from the University of Tennessee's Tickle College of Engineering. The study provides data regarding the aggregate and subsector manufacturing industry of the United States found in literature for quantitative depiction. Use of trade names and company products in the text are intended to provide adequate information for procedures used only, and do not imply endorsement of products.

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Chapter One

INTRODUCTION AND GENERAL INFORMATION

Introduction

To remain competitive in a dynamic marketplace, the need for companies to innovate in process, not only product, is becoming increasingly important. As improvements in electronic capabilities and unit costs continue to be made, the integration of technology with machinery and processes has led to a new revolution in manufacturing, commonly referred to as Industry 4.0 (Morgan, 2014). Key drivers of this movement include concepts such as 'big data,' 'the internet of things,' and 'advanced manufacturing.' The focus of this movement is to link technologies together and perform statistical analysis on accumulated data in real-time to make informed decisions automatically. The end goal is seen to be closed-loop, lean systems that perform at optimal efficiency. Efficiency, in this sense, refers to an entity's ability to understand demand, create or align a fulfilling product or service, and supply that offering in the most time and cost effective manner possible. This efficiency stretches from machine control to a company's end-to-end supply chain. As such, investment in Industry 4.0 technologies is expected to increase significantly over the next decade. Pricewaterhouse Coopers estimates industrial sectors in the United States to invest $907 billion annually in Industry 4.0 technologies (Geissbauer et al., 2015). A primary component of the advanced manufacturing branch is the development of 'additive manufacturing.'

Industry leader EOS defines additive manufacturing (AM) as "…a process by which digital 3D design data is used to build up a component in layers by depositing material" (EOS, 2016). Commonly known as '3D printing,' AM technologies are revolutionizing part design and manufacturing potential for polymers, metals, cement, and biomaterials alike. A $2 billion industry in 2012, analysts predict AM to grow by 300% over the next decade, even as component costs decrease (Zistl, 2014). Additive manufacturing provides unique capabilities to produce customized, complex parts, shorten lead-time, reduce weight, improve sustainability efforts, and reduce material waste when compared to traditional manufacturing (TM) processes. Primary sectors currently investigating and using AM technology include the aerospace, aeronautics, medical, automotive, construction, and military industries. By implementing this technology, companies may provide customized products or replacement parts to customers at little to no additional cost.

The high revenue potential available in the market has led to a boom in research and development efforts. While hundreds of start-up companies have been created for polymer machines, only a handful of options exist for metal machine manufacturers, primarily due to the capital investment required (Lansard, 2016). Companies such as Arcam, EOS, SLM Solutions, ExOne, Sciaky, Optomec, and ConceptLaser lead the global metals industry, each providing unique process capabilities. As a result, commercial companies must decide which process and corresponding machine manufacturer best meets their individual needs.

Despite continuous improvements made in AM technologies, there remains significant corporate reluctance and hesitancy towards investment in metal additive manufacturing machines for production and tooling needs. Aside from time requirements and build volumes currently available, primary concern focuses around reliability in part quality. Defects in porosity, surface finish, material strength, and microstructure are more prevalent in AM than traditionally manufactured parts (Frazier, 2014). Further, variability exists between parts within the same build, parts between builds, and parts produced on different machines (all with the same machine settings and part design). Combined with the high initial costs for the machine (typically in the high six-figure to seven-figure pricing area), material, overhead, and technician training, the uncertainty towards quality annual output leaves many companies to conclude that additive manufacturing is too risky and not a viable investment at its current state.

Similarly, polymer machines such as MakerBot, 3D Systems, and Stratasys can produce parts for rapid prototyping or molding at significantly lower costs – desktop units are available for several hundred dollars, while high-end machines can price in the low to mid six-figure region. However, there remains reluctance for industrial use primarily due to associated material property concerns. As a result, corporate and industry innovation is often hindered.

Thus, it becomes relevant to assess how to approach the business case for additive manufacturing. Corporate strategy and investment decisions require leadership support and statistical evidence of expected outcomes. Essential to the approach is the accumulation of data and quantification of expectations.

Purpose

Background and Motivation for Research

Motivation to conduct this research arose from the author’s interest in additive manufacturing and the technology’s progressive influence on the industrial marketplace. Having worked in both traditional and additive manufacturing environments, along with study of operational improvement, researching the business case between the two provides a unique blend of experience and education. The current and potential viability of the processes covered is recognized to have significant impact on current and future corporate operational structures and supply chains, rendering the study useful for industrial purposes. Further, the ability to present an evaluation procedure in a manner accessible to non-technical audiences promotes its effectiveness of being used for corporate purposes.

Research Approaches and Gap Remaining

To drive data collection, cost estimation of additively manufactured production parts is typically conducted (Hopkinson and Dickens, 2001; Lindemann et al., 2012; Ruffo et al. 2007). Many academics associated with the field have discussed the business case for AM and provided associated cost models (Ponfoort and Krampitz, 2015; Thomas and Gilbert, 2014). These mathematical models are often combinations of subcost models comprised of machine costs, material costs, energy costs, build times, and production units. However, there are additional costs involved that are not conventionally factored into costing models that can provide more accurate insight into reality. Additionally, there exist complementary revenue streams capable through switching production to additive manufacturing. Even as several discuss the trade-offs between additive and traditional manufacturing techniques, they do not provide a guideline for an investigative company to follow. The literature gap, therefore, lies in the accumulation of necessary and relevant investment analysis, how that information drives decision-making, and how that process is outlined for use by non-technical or non-industry audiences.

Objective of Thesis

The objective of this thesis report is to address the literature gap by providing a reader-friendly evaluation process, incorporating descriptive costing models for AM processes, and providing a set of financial and operation indicators by which to gauge decisions. As a component of this analysis, key drivers of both cost and decision making will be identified, and a listing of required data collection will be presented. This required data set will identify the information needed for an investigator to be able to perform an introductory analysis.

Hypotheses Presented

It is expected that the study will indicate reliance on individual case context; however, several common themes identified in literature shall hold true. Namely, that AM is currently most viable for small to medium series part production, with parts involving a high degree of design complexity, or parts of specialized materials, in which waste reduction drives savings. While some may be able to benefit from AM in its current form, other options will remain more economically feasible for others until the technology improves.

Scope and Approach

Scope of Work

The scope of work entailed in this thesis project is confined to providing a functional process methodology, through which a general user can follow and apply to evaluate whether they should invest in additive or traditional manufacturing for production purposes. This includes conducting a review of relevant literature, formulation of a process, and demonstration through a case study. Approach methodology and results shall be conveyed in the deliverable of this thesis report, by which a defense presentation will be held with the author's graduate committee to determine acceptable completion of project and candidacy for graduation and conferment of degree.

Organization of Thesis

The organization of this thesis document is divided into five primary content chapters, with acknowledgements, an abstract, preface, and lists of tables and figures preceding. References and vita are adjoined to the end, as corresponding with the table of contents. The structure of the five content chapters are intended to provide general information, background on the topic, process development and methodology, a case study application, results and discussion, and a conclusion with future recommendations. The general information section provides the context in which the thesis was written. Topic background contains a general literature review of traditional manufacturing, additive manufacturing, and development of the business case between the two. Process development and methodology provides the suggested procedure for evaluation, including the general costing and valuation equations. A case study is used to demonstrate application of the process, and to provide a means to obtain quantification data for analysis. Case study elements, applied within the context of the procedure introduced, generate the results needed for analysis. Discussion of the results will help identify key drivers and general observations. Finally, the conclusion section will summarize the objective and outcomes of this thesis report, and provide discussion regarding future improvement recommendations.

Validation of Thesis

Due to resource constraints, the procedure and methodology were not able to be tested for validation with real-world part production and study. As such, effectiveness of methodology is determined via case study application and comparison to test results reported in the literature. It should be acknowledged that error will exist between theoretical modeling and realistic application. A path taken to address this is to perform sensitivity analysis to gauge baseline and pessimistic results.

Chapter Two

BACKGROUND INFORMATION

The number of literature articles concerning additive manufacturing has increasing significantly over the past couple of decades. Article publications increased from an estimated 1,600 in 2011 to 16,000 in 2012 (Ford, 2014). The approach taken to conducting a review of the literature was to search for digital articles available on Google Scholar and through access to the University of Tennessee's online library databases, inclusive of Scopus, Business Source Complete, Web of Science, and the general OneSearch database search tool. Search terms used included text related to the business case for additive manufacturing, additive manufacturing costs, traditional manufacturing costs, and more specific background information searches, such as the categories of additive manufacturing or understanding voxel approximation methods. Additional articles were identified through citations and references listed within text. General industry information was elicited through a general Google search for publicly available, yet reliable statistics. The thesis author tried to locate literature proposing multiple approaches or disagreements towards a topic to ensure understanding of the topic's context and arguments presented.

Manufacturing Industry

The United States Congressional Research Service reports, as of January 2017, the United States held 18.6% share of the global manufacturing industry in 2015, making it the world's second largest manufacturing country behind China (see Figure 2.1). Much of this difference, and the U.S.'s market fluctuation over the past decade, can be attributed to the changing value of the dollar. Despite a recent push for U.S. companies to offshore manufacturing operations and a coinciding decrease in manufacturing employment, manufacturing output has been growing, although slowly, in the United States. As such, the U.S. manufacturing sector generates $2.17 trillion in annual economic value added, 12% of total U.S. gross domestic product (see Figure 2.2). Approximately 11% of this value add is spend on research and development, up from 8% in 2002. "Value added attempts to capture the economic contribution of manufacturers in designing, processing, and marketing the products they sell…value added can be calculated as total sales less the total cost of purchased inputs…" adjusted for imports (Levinson, 2017).

Additive manufacturing collected an estimated $967 million globally in 2013. The United States accounted for $367 million of that total, 38% of total AM production. Estimates report that the AM market achieved an 8% market penetration in 2011; however, this only represents between 0.01 – 0.05% of goods produced in relevant industry subsectors, indicating substantial room for growth (Thomas and Gilbert, 2014). Over the course of twenty-three years (from 1988-2011), the U.S. accounted for 38.3% of the cumulative

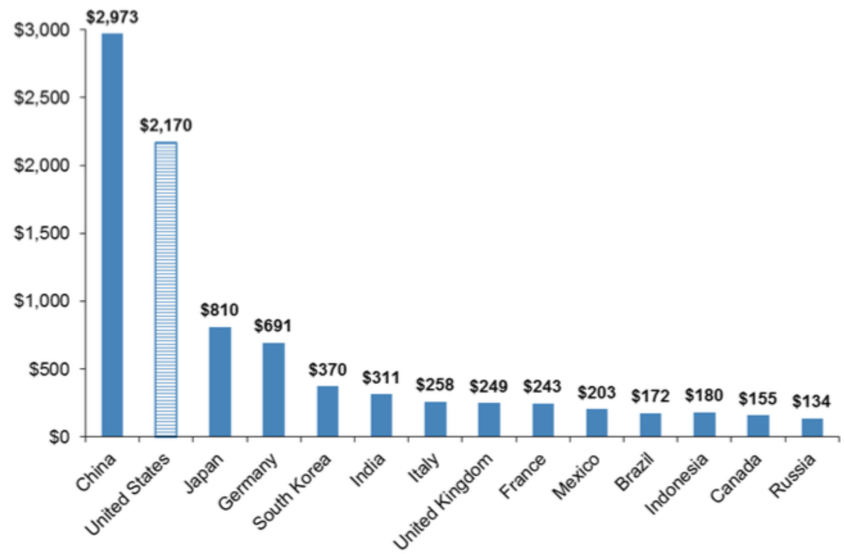

Figure 2.1 Value added by manufacturing, in billions of dollars, 2015 (Levinson)

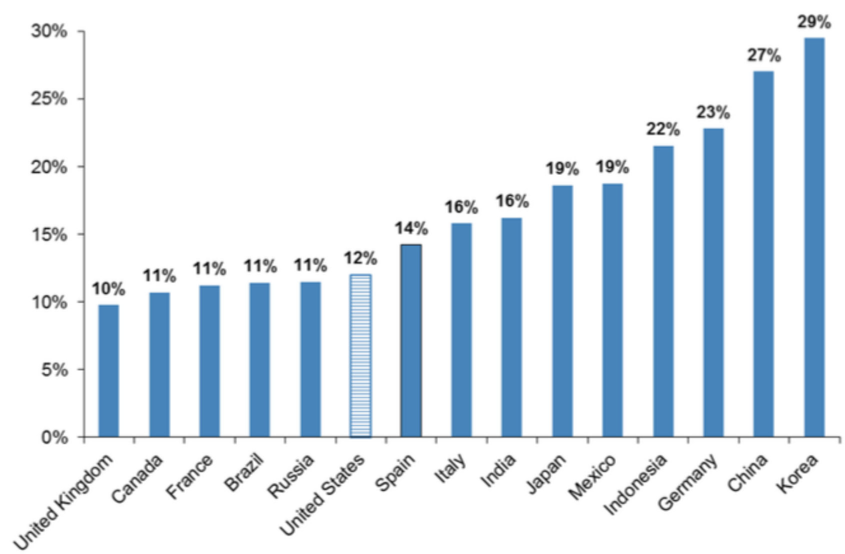

Figure 2.2 Manufacturing value added as a percentage of GDP, 2015 (Levinson)

additive manufacturing machines installed globally, as shown in Figure 2.3. The leading sectors for these machines are the automotive, medical, and aerospace industries, with sector weight information shown in Figure 2.4. The United States International Trade Commission indicates "…the most significant factors affecting the potential of additive manufacturing to contribute to U.S. competitiveness are developing standards, improving the selection and affordability of materials, and increasing the accuracy and reliability of equipment and processes." In the pursuit of addressing these setbacks, organizations such as AmericaMakes have been formed as a collective public-private partnership amongst government, industry, and academic sectors (Ford, 2014).

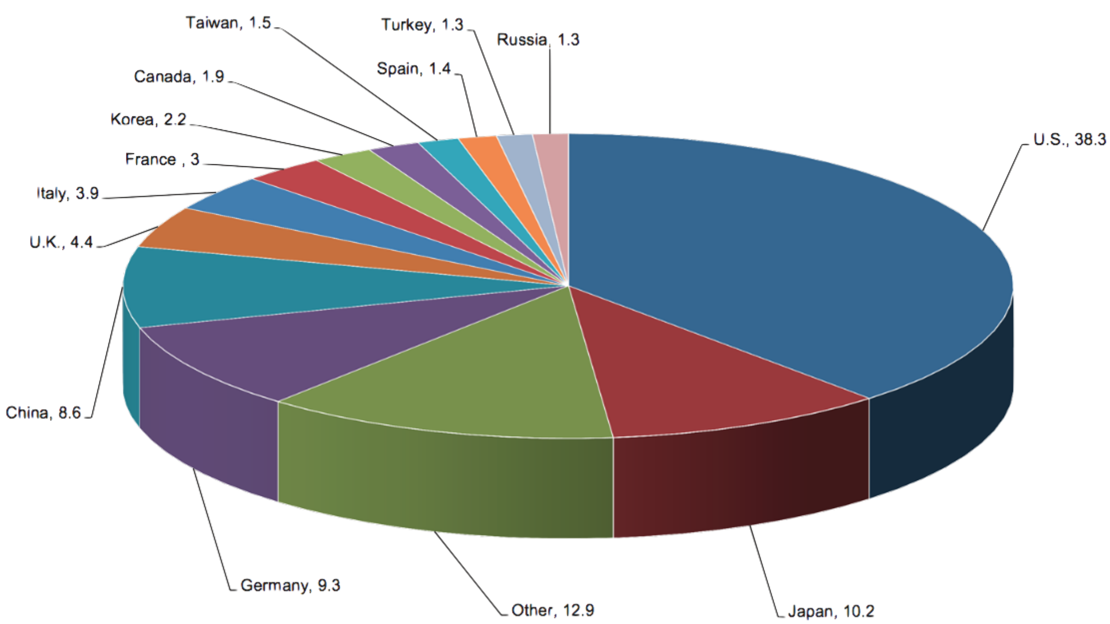

Figure 2.3 Additive manufacturing machines installed by country, 1988-2011 (Ford)

Considering the market size available, in conjunction with the direct and indirect benefits made possible, additive manufacturing will remain a growing field. As the technology matures, it becomes a new source for manufacturing competitiveness in product, organization, and country (Petrovic et al., 2011). To understand the context for which AM adoption can impact manufacturing, we must review both additive and conventional manufacturing processes. Only then can one see the trade-offs achievable between the two approaches to manufacturing.

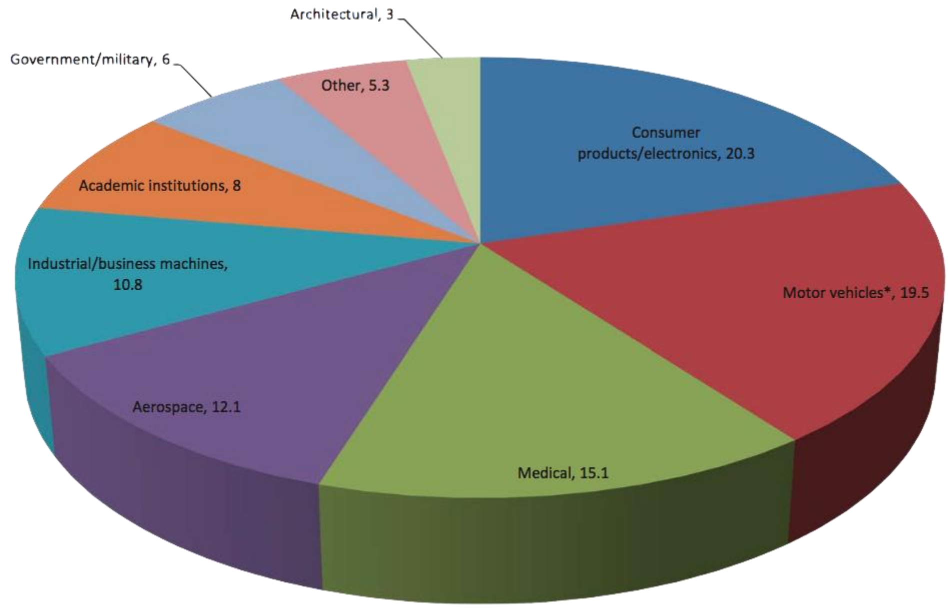

Figure 2.4 Additive manufacturing industrial sectors, 2011 (Ford)

Manufacturing Processes

Overview of Conventional Manufacturing

Conventional manufacturing (CM), also known as traditional manufacturing (TM), typically refers to the standard manufacturing methods of casting and molding, imaging and coating, forming, machining, and joining (Gutowski et al., 2006). In this, a set of drawings are created or drafted indicating shape, dimensions, tolerancing, material property requirements, and special attributes for fabrication of individual parts and systems.

Casting and molding consist of various processes in which material is melted or dissolved into a liquid, and subsequently poured into a mold or cavity of set shape. Upon cooling, the solidified material will match the form of the mold or cavity. The primary difference between casting and molding designations is that molding uses internal or external pressurization, whereas casting does not. Commonly cast products include metal dies, concrete, and plastic resins; commonly molded products include bottles and packaging, usually made from plastic (Dalquist and Gutowski, 2004).

Imaging and coating typically involves surface alteration processes in which a material is applied to or cut from an existing structure. Examples of imaging include laser engraving or etching, as in text or symbols cut into a part’s surface. Coating is application based, as with plating, printing, and spraying processes.

Forming refers to altering the shape of a metal or non-metal without breaking it. Methods involved include forging, rolling, extruding, pressing, bending, and stamping. Forming is often used in making metal buckets, cookware, support structures, and providing shape to raw materials (i.e., rolled steel).

Machining comprises the forming or shaping of solid materials by cutting or removing material. Machining can include surface milling, turning, drilling, tapping, sawing, cutting, routing, grinding, polishing, and blasting process amongst other methods and variations. In the context of additive manufacturing, machining is often viewed as the converse, or subtractive manufacturing, as material is being removed. A few examples of this process include turning wood on a lathe, boring and tapping holes, surface finishing, and cutting contours into solid material.

Joining is the conventional manufacturing technique most closely related to additive manufacturing as materials are joined together by a solidified liquid or plasma bond, or via mechanical means. This method includes various types of welding, soldering, sintering, fastening, adhesive bonding, and press fitting. Examples of products manufactured by joining includes the bolting of wooden beams, welding of metal joints, connecting electrical wires, and gluing materials together.

Overview of Additive Manufacturing

Additive manufacturing (AM) encompasses several processes that create three-dimensional (3D) parts and structures through a series of stacked part cross-sections. Key steps of this process include the generation of one or multiple part file(s), positioning the part(s) on a build plate, printing the part(s), part removal, and post-finishing.

The process typically begins with the creation of a 3D computer-aided design (CAD) model. These part models and assemblies can be created with commercially available software such as Autodesk AutoCAD or Dassault Systemes SolidWorks, usually in a .STL [stereolithography] file format. In a sense, the collection of two-dimensional (2D) drawings used in conventional manufacturing is translated into a single 3D part file (Rosen, n/a).

The model file is then pre-processed by separate software, such as Materialise Magics. In this step, the model is oriented for production on the build plate, and support structures are generated, where needed. It is important to consider orientation to optimize the number of parts capable of being printed in a single build, the overall time required, material properties associated, surface finish, and the amount of support material needed. These support structures are used in some processes to provide a solid substrate on which material may form, often areas with some form of overhang, and for thermal energy dissipation. Support material can additionally be used for spacing purposes between parts and even the build plate. This allows parts to be ‘nested’ such that parts can be created on top of other parts and for easy removal.

Once the part(s) has been positioned on the build plate in the software, it is 'sliced' into layers of cross-sections with a given thickness. The thickness corresponds to the parameters associated with the respective AM method. The number of slices indicate the total z-height (height from the build plate surface to the top-most point of a part) divided by the determined thickness setting. This pre-processing software also allows for resolution to be set (the degree of fineness required). Next, all slicing information and parameter data are exported in a .SLI, .SLC, or specialized format that corresponds to the processor installed on the AM machine tool. At this point, the file is 'printed' slice-by-slice by one of the AM process methods to form the model set (Petrovic et al., 2011).

The American Society for Testing and Materials (ASTM) International Committee F42.91 on Additive Manufacturing Technologies identified seven primary methods of AM, as listed in the ASTM F2792 standard. These seven methods are binder jetting, directed energy deposition, material extrusion, material jetting, powder bed fusion, sheet lamination, and vat photopolymerization (Thomas and Gilbert, 2014).

Binder jetting is an AM process in which a liquid bonding agent is selectively deposited to join powder particles in a pattern consistent with the part's cross-section of the respective slice (ExOne, 2017). After the print head drops binder into the powder, more material is spread across, as the build plate drops, to allow the next layer to be set. The completion of all slices results in the formation of the 3D object. This process can be easily compared to building a structure out of sand and glue. The completed object is then removed from the machine and often cured in an oven. In curing, the binder material is typically vaporized, leaving behind the desired material that can become sintered together. Binder jetting is applicable to a range of material powders including metals, plastics, ceramics, and sand. Primary uses include prototyping, small series part production, and developing casts and molds. Commercially available machines include models from vendors Voxeljet, ExOne, and Zcorp.

Directed energy deposition (DED), also known by 'laser engineered net shaping,' 'direct metal deposition,' 'laser freeform fabrication,' and many others, is a deposition, melting, and solidification process, typically with metals. In this, an energy source, often a laser, electron beam, or plasma arc, melts deposited powder or wire feedstock along the slice pattern, typically in an inert gas environment (Gibson et al., 2010). In this case, either the energy nozzle or the build plate is attached to a four or five axis robot to enable multi-dimensional movement. Much of the material science behind this methodology is comparable to conventional welding. DED is useful for repair work and fabrication of large, net-shaped parts. Commercially available vendors include Sciaky, Optomec, and DM3D.

Material extrusion refers to machines that push material through a nozzle and onto a build platform, with either the nozzle or platform moving in three-dimensional space. The most common form of material extrusion is called 'fused deposition modeling' (FDM). In FDM, a thermoplastic filament or collection of pellets is melted at the tip of an extruder nozzle and pushed onto the build platform, corresponding to the respective slicing pattern. As the slices are deposited and cooled, the object is built. Extrusion printers can handle a large variety of thermoplastic and specialized materials. This process is useful for prototyping, small series part production, and some casts and molds. Commercial machinery covers a wide range of size, speed, and costs, from numerous vendors such as Stratasys, LulzBot, MakerBot, Ultimaker, and Cincinnati.

Material jetting describes the process by which a printer head deposits or drops subsequent layers of liquefied material onto a substrate, where it cools and sets into the net shape. The final product is often cured with ultraviolet light. Material jetting can accommodate both polymers and metals. Typical use is similar to binder jetting and extrusion printers, for prototypes, casting patterns, and small series parts. Manufacturers following this approach include 3D Systems, Stratasys, and Vader Systems.

Powder bed fusion is a group of processes in which material powders are sintered or melted together to form a solid part. Other terms affiliated with powder beds are ‘electron beam melting,’ ‘selective laser sintering,’ selective laser melting,’ and ‘direct metal laser sintering.’ In powder bed fusion, a layer of powder is spread over a build plate, often in an inert environment, at which point a laser or electron beam energy source selectively fuses the powder particles together, according to the shape of the part slice. Once all slices are processed, excess powder is collected, and the part is removed. Most powder bed systems are designed to process metals and alloys, while few use plastics. All are typically used for prototyping and small series production, particularly with parts requiring a high degree of complexity. Industry leading vendors of this technology type include Flashforge, EOS, SLM, Arcam, Renishaw, and ConceptLaser.

Sheet lamination is a method involving layers of sheets or ribbons, cut into form, and bonded together. ‘Laminated object manufacturing’ and ‘ultrasonic additive manufacturing’ are two additional terms used. In this process, material sheets are subsequently stacked on top of each other, where a laser or cutting blade removes material not indicated on the slice file. The resulting stack of layers are then bonded together by an adhesive, thermal bonding process, clamping, or ultrasonic welding. Sheet lamination is primarily viable for scaled parts and conceptual parts of limited metals (Gibson et al., 2010). Industry manufacturers include MCor Technologies, Cubic Technologies and Helisys.

The seventh category of additive manufacturing is vat photopolymerization. In this process, ultraviolet light is directed across a vat of liquid resin, curing the material in accordance to the shape of the cross-sectional slice. This technology is typically used for scale models and concepts. Manufacturers available include 3D Systems, EnvisionTEC, and Ilios (Gibson et al., 2010).

Benefits and Limitations

Perhaps the most important advantage of conventional manufacturing is the degree to which its processes are understood. With many techniques existing for centuries, conventional manufacturing offers the consistency and control needed to mass produce goods. Technologies such as computer numeric control (CNC) enable traditional machinery to be programmed and automated to operate with extreme accuracy. Additionally, this depth of understanding provides consistency in material properties, allowing for periodic quality assurance measures and a basis product design. The universal nature of conventional manufacturing methods provides easy transferability and understanding across markets, enabling complex supply chain structures.

However, conventional manufacturing often requires incorporating several processes to produce a good. Depending upon the extent to which this is required, high initial costs can be encountered. As such, it is common for a company to possess the equipment and sell their services to others. A potential drawback of this, however, is the potential costs associated with transporting the goods, and can cause long lead times. One of the most important issues present is the amount of waste material produced. Particularly with milling operations, excess material is cut away in the form of 'chips.' While recent efforts are being made to recycle or repurpose this material, much is expensed as waste. Depending on the material used, disposal of waste can have additional costs beyond the value of the material, as seen with hazardous materials.

Addtitive manufacturing concepts address some issues present in industry, but introduce new challenges as well. The main benefits offered by AM include design complexity, weight and waste reduction, potentially shorter lead times, simplified material sourcing, and localized manufacturing. Corresponding issues encountered include consistency, inferior material properties, need for post-processing, potentially long lead times, high start-up costs, and a lack of standards (Conner et al., 2014; Hopkinson and Dickens, 2003; Levy et al., n/a).

A popular saying for AM is that it provides 'complexity for free,' meaning no additional cost is incurred by adding complex geometries and features to part design (Conner et al., 2014). Additive manufacturing provides unique capabilities to produce lattice structures, internal cavities, embedded text, and even internal watermarks. Through the use of topology optimization, parts may be redesigned to exhibit the required mechanical properties at the optimal material and cost balance (Campbell et al., 2012). Lattice structures and internal cavities are useful in reducing part weight while still maintaining strength. By such methods, hollow parts may be easily created with internal, load-bearing structures. Internal passage cavities also allow for unique fabrication capabilities for wire routing and fluid flow. Casting dies and other systems can correspondently be designed for optimal thermal control. As a result, many product fabrication lead times may be reduced, as the AM machine generates the features conventional manufacturing would require several machines to achieve.

Further, being able to generate a variety of features in one machine allows for portability and localized production (Khajavi et al., 2013; Mashhadi et al., 2015). The key advantage of this ability is that a machine may be placed in remote areas, such as on a ship, so that spare parts, tooling, and other needs may be created on-site as needed; through this, lead times for part manufacturing and transportation can be significantly reduced, not to mention the protection of information. From a corporate perspective, localized production can also mean that customized parts may be provided local to customers to achieve similar transportation and time to market savings.

From a sustainability perspective, because material is only fabricated either where it needs to be for the part, or in support of the part, AM significantly reduces the amount of material waste collected from manufacturing. Whereas conventional milling generates waste chips, nearly all the raw material external to the part may be reused in AM. Sources of waste material through AM is typically comprised of support structures, soot or fused particulate, and any material removed by post-processing. This extra material is often removed via abrasive, chemical, or mechanical means. Additional sustainability efforts present in the literature include reduction in manufacturing emissions and energy usage. Research is also being conducted to incorporate biomaterials into AM, further extending its environmental conservancy (Chen et al., 2015; Ford, 2014; Gebler et al., 2014).

While many benefits are accessible through additive manufacturing, current issues hinder its adoption. The consistency in geometry and material properties are a big concern for AM when compared to CM. Parts generally have a comparatively rough surface finish, often requiring some form of finishing, such as abrasive blasting or milling. Also, largely due to powder particle morphology, infiltration of soot particulate, and variations in thermal cycles, material defects such as porosities, swelling, and residual stresses can lead to inferior material properties; among these include warping and fracture, density, yield strength, and grain homogeneity (Levy et al., n/a). While some post-finishing processes are used to alleviate some deficiencies, such as hot isostatic pressing, others can render a part inadequate for use.

A different consistency issue occurs with reliability. It is well-noted that variations in part properties exist from part-to-part, build-to-build, and machine-to-machine. By this, two parts produced in the same batch, or at different times, will likely not exhibit the same geometrical and material properties. This creates a nightmare for quality assurance groups looking to ensure product safety. Further, because no common set of standards exist for reference, companies struggle to qualify parts and procedures for validation and verification.

Other issues faced include potentially long lead times, build volumes, and high investment costs. Due to the layer-by-layer scanning strategy used in AM, large and dense parts can require a significant amount of time to complete. While trade-offs of complexity may still yield AM the most cost-effective production method, processing may take longer than conventional methods. Also, most current machines are limited in the product size they can produce; powder bed machines, in particular, due to their powder layering mechanisms and typical inert atmosphere requirement. Wire-feed and several deposition systems, however, are capable of constructing larger structures. Finally, the current state of AM requires high initial investment costs. Most industrial machines come with a six to seven figure price tag and require significant time for process development and understanding. The expenditure for procurement, labor, facilities, and testing – all necessary for process understanding before valuable parts are created – can require additional resources and consideration before investing.

Adoption of Additive Manufacturing

These concerns and inconsistencies often prevent commercial industries from investing in additive manufacturing. However, many don't account for complementary value obtainable. Ford claims, "Firms that employ additive manufacturing are beginning to achieve benefits such as increasing supply chain efficiencies; reducing time to market; moving from mass production to mass customization; and sustaining the environment" (Ford, 2014). These factors, though difficult to quantify, are important in analysis. Adoption by corporate entities will be an important step in the development of AM, as conventional manufacturers may apply industry knowledge and techniques, along with economies of scale. If successful, AM barriers to entry (often investment costs and consistency concerns) may be reduced enough to enable wider commercialization. The end-goal will be to make AM processes as controllable as conventional methods are.

With the current state of AM, time is needed upon machine acquisition for setup, equipment familiarization, and development of parameters. Original equipment manufacturers (OEM) often provide a basis for parameter settings, however, confirmation of material properties and corresponding parameter adjustment are necessary. This time is also useful in testing design features, enabling product design technicians to understand design freedom available.

After installation and development, it is useful to monitor the machine performance for reliability and maintainability purposes. As such, a variety of sensors are available to monitor values such as oxygen concentration, temperature, melt-pool optics, and gas flow. A popular desire is for all sensors to be synchronized and monitored in real-time, allowing the machine to become a closed-loop, autonomous system.

Developing the Business Case

Several in the literature promote the development of the business case for additive manufacturing (Ponfoort and Krampitz, 2015; Thomas, 2014). As a potentially disruptive technology for several industries, due to its capabilities to reduce costs and generate value addition, many are currently investigating its viability. Gartner lists enterprise AM in the 'slope of enlightenment' region of their 2015 technology hype cycle chart, shown in Figure

2.5 (Rivera and van der Meulen, 2015). Due to the demand for information, academics have introduced different approaches to cost structure and component estimation models (Ben-Arieh and Qian, 2003; Ozbayrak et al., 2003; Toktay and Wei, 2005). However, most only report on cost modeling, and do not provide information regarding potential cost savings and value generation, such as sustainability and supply chain effects (Khajavi et al., 2013; Mashhadi et al., 2015; Chen et al., 2015; Gebler et al., 2014). Thus, to provide a more realistic analysis, both cost and value should be incorporated.

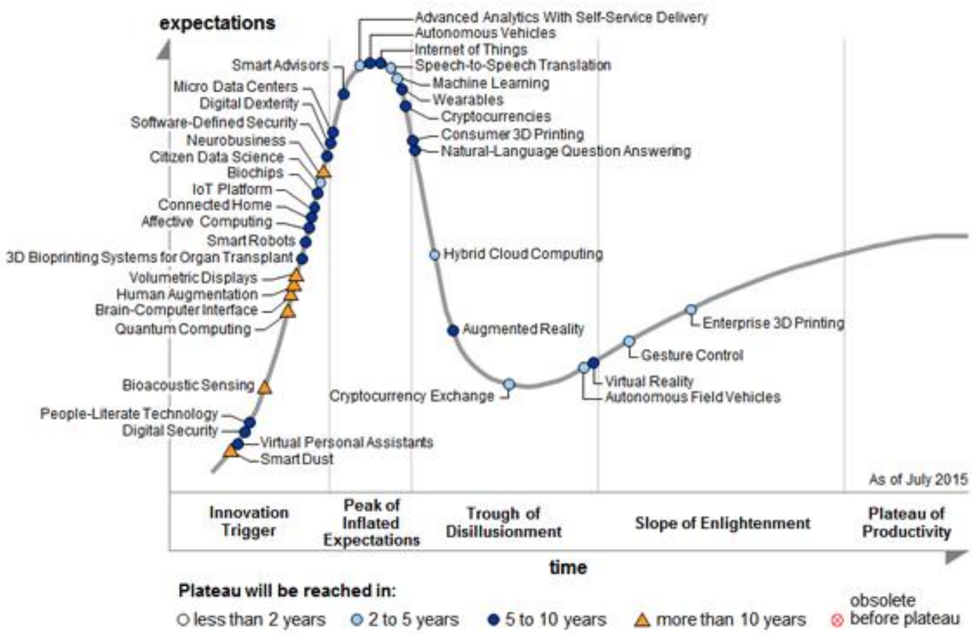

Figure 2.5 Gartner's hype cycle for emerging technologies, 2015 (Rivera)

Also, there exists several approaches to adopting additive manufacturing technologies (Karunakaran et al., 2010). While this report focuses on investment in purchasing an AM machine tool, companies may alternatively solicit production from a service provider. Although overhead and equipment costs are still incorporated into service costs, the investigating firm would not incur the associated risks of ownership, nor need to develop the parameter sets for the machine. This is particularly useful for one-off parts.

Operational and Financial Indicators for Decision Analysis

Apart from cost or profit comparison, several financial and operational indicators are useful for evaluation. Operational indicators include throughput and lead time. Throughput rate is a measure of how many parts can be produced in a given amount of time, while lead time is the amount of time required to make a product, from process initiation to final completion. Financial indicators include breakeven analysis, return-on-investment (ROI), and present worth (PW). Breakeven analysis reports the estimated amount of time or part units required for the part’s contribution to profit to equal the fixed costs of investment. ROI and PW are both analyses of expected cash flows over the lifespan of the investment. ROI provides an overall rate of return, useful for companies that have minimum return acceptability policies. Meanwhile, present worth provides an indication towards whether or not the investment is expected to be profitable over its lifespan.

Several important acknowledgements need consideration in review of generated values, specifically regarding context and accuracy. The approach and models proposed should be interpreted within individual context, as different parts, companies, and industries approach certain estimates differently. Additionally, estimates often differ from real-world application, particularly in consideration of the need to understand the equipment and processes. As such, sensitivity analysis should be conducted to provide a more realistic range of expectations. In this, certain parameters are varied to study how change affects other output characteristics. It is by sensitivity analysis that the literature concludes conventional manufacturing to be more appropriate for large volume part production (Ponfoort and Krampitz, 2015; Ruffo et al., 2006).

In consideration of the sensitivity analysis and performance indicators, investment decisions may be made. If the process is not able to meet production requirements, as determined by annual production or throughput rates, or if the breakeven point occurs beyond the lifespan of the investment, then the data implies AM is likely not a good investment for the part and system under consideration. Alternatively, if the ROI is positive and above the individual’s required rate of return, or if the present worth is positive, then AM should be considered for investment. If the initial analysis indicates that investment is viable, then a real-world study should be conducted by quantifying the factors generated by real production, and subsequently re-evaluating with the realistic data. This entire process will be covered more in-depth in the text following.

Chapter Three

PROCESS DEVELOPMENT

From review of the literature findings and consideration of real-world experiences, a process is proposed to facilitate evaluation of additive manufacturing for production investment. It is important to note upfront that much of the analysis will be case dependent as different entities assign different values to costs, investment criteria, priorities, current system approaches, and the general nature of the part under review. This chapter provides a guideline which an entity could follow in their own, respective analysis. The approach taken is focused on investment in AM equipment, but procedures will be provided when applicable regarding alternative routes.

The procedure identified herein will be provided and explained cumulatively and in part. The proposed process may be divided into nine functional steps – three data deterministic, three calculation based, and three review based. The process steps are as follows: 1) identification of suspect parts, 2) quantifying potential processes and machines, 3) determining current production information, 4) approximating additive manufacturing capabilities, 5) comparing financial and operational expectations, 6) performing sensitivity analysis, 7) initial judgement, 8) performing a validation case study, and 9) making a final decision. Figure 3.1 provides a graphical depiction of processes.

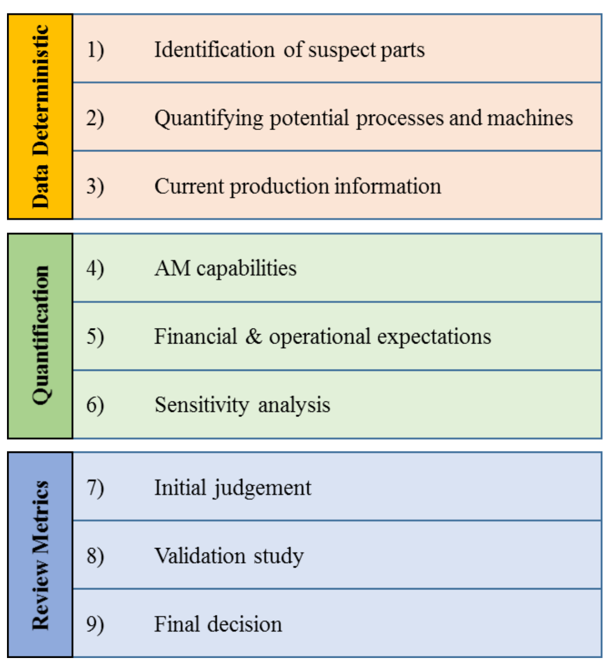

Figure 3.1 Proposed AM evaluation process

The author acknowledges part and machine quantification can be applied in the alternate order (i.e., suspect part selection is determined based on machine capabilities). The decision to list part identification first primarily arose out of the context for initial investment. An entity purchasing a machine and then figuring out what to do with it holds a less stable justification for investment than identifying a need and eliciting a quantified argument that investment will fulfill that need.

It should also be noted that, as with most estimation models, inaccuracies will exist between the evaluation output and real-world application. While the process and mathematical models are designed to be flexible enough to absorb some of this error, it should nevertheless not be overlooked. Sensitivity analysis is done in recognition of this to provide a more accurate representation of outcome expectations. As in any investment evaluation, the author encourages users to seek additional information.

For this analysis, several conventions need to be recognized on approach. First, a standard Cartesian coordinate system is used, in which the ‘x’ and ‘y’ axes define the horizontal floor plane, and the ‘z’ axis indicates the vertical extension, as shown in Figure 3.2. Second, some variables require additional determination by the user, reflective of their individual situation. Finally, this methodology may be conducted with substitution of other cost estimation formulas present in the literature (Baumers et al., 2012; Niazi et al., 2006; Ruffo and Hague, 2007; Shehab and Mason, 2001). This method is intended to provide a basic quantification of the business case. As such, it is acknowledged that more accurate cost modeling equations exist in the literature, but they are typically more calculation intensive. In particular, many AM cost models incorporate summation notation across the individual layers in a given build (Byun and Lee, 2006). In comparison, the method described below takes a volumetric approach for quicker, and simpler evaluation.

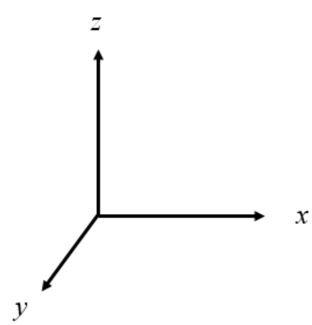

Figure 3.2 Three-dimensional Cartesian coordinate system

Preliminary Evaluation

Identifying Suspect Parts

The first step in the evaluation process is to identify a part or set of parts that are potential candidates for additive manufacturing production. Typically, these parts are relatively small in size and/or complex in geometry. Alternatively, they could be regular replenishment parts needed for tooling and other machinery (Ponfoort and Krampitz, 2015). Intended production approach should be considered, as to whether the potential machine will be dedicated to production of one part type, or if it will be used for multiple parts. Because different machines and processes are more appropriate for different types of parts in terms of method or build volume, one machine may be better for singular production, whereas another might be more appropriate for an aggregate. Also, consideration of material type is needed. Material change-over can take several days for some machines, while a matter of minutes for others. If all parts are to be made of the same material, then change-outs can be ignored. However, if parts require different materials, particularly with metals, change-overs should be factored in for time requirements. If it is the first time with a new material, additional time may be required to determine acceptable machine parameters.

With each suspect part identified, we may develop a bounding box as shown in Figure 3.3 that contains simplified geometric information regarding the size and shape of each part. This bounding box is essentially an extrusion of the part's shadow, if the light source were placed directly above the part, and extended along the z-axis to the maximum part height. The shadow is a cumulation of all perimeters in the xy plane along the z-axis. While the shadow may be rough and complex in geometry, it must be reduced to a common polygon to simplify calculation. In many cases, it suffices to create a rectangular prism encompassing the part (similar to bar stock). Note that if the reviewer has a specialized software package, they may be able to obtain specific boundary box information from the software.

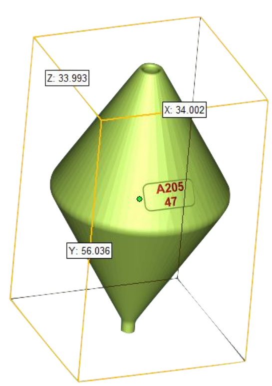

Figure 3.3 Rectangular prism bounding box depiction around part

At this point, it is important to consider part orientation. Part orientation, in many cases, can significantly effect production volumes and costs, as it determines the number of parts capable of being placed on a single build plate, the overall build height, and the location and amount of support material; these have direct impact onto build and part costs. The reason we need to consider orientation this early in the process is to ensure a single part can fit within the bounds of a given build volume. Because tensile strength is typically weakest along the z-axis, it may be necessary to position the part in a particular orientation to accommodate load expectations (Gibson et al., 2010). While several part orientation algorithms exist in the literature, it may often suffice to resort to simple observations (Hur et al., 2001; Nyaluke et al., 1996; Zhang et al., 2016). If permissible, a part may assume one of four general orientations, respective of a given part surface: on a side, lying flat, sitting upright, or at an angle – as shown in Figure 3.4. Note that changing the part orientation changes the shadow on the floor of the bounding box.

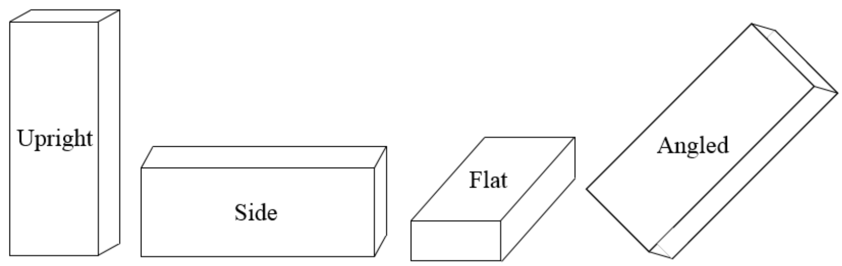

Figure 3.4 Part orientations on build plate

From the bounding box, we may obtain several key variables regarding the part dimensions. The shadow polygon provides the cross-sectional area (a_{cs}) space required by a part on a build plate. The height of the bounding box along the z-axis (h_{box}) correspondingly determines the overall build height. From these values, the volume of space required by the bounding box (v_{box}) may be calculated according to equation (1) below.

$$v_{box} = a_{cs} * h_{box} \tag{1}$$

This bounding box volume (v_{box}), however, does not accurately reflect the actual part, only the amount of space needed for it, assuming no parts are permitted to overlap in a multi-part build (in the case parts can overlap bounding boxes, such as with unique features, the overlap region should be excluded from bounding box calculations). Due to empty space present around the part but contained in the bounding box, the volume of the part (v_{part}) must be isolated for subsequent calculations. While this volume could be calculated mathematically, it is simpler, and arguably more realistic, to locate the part volume through special features of CAD software (the software can output the volume of the model), measured submersion in a known volume of fluid, by 3D scanning the part, or other mechanical means.

Quantifying Machinery

Once a suspect part or set of parts is identified, the reviewer should determine which AM processes are suitable, according to the part's material. The minimum acceptability criteria in this phase are the material properties reported by both the manufacturer and industry users. If the machines are not capable of producing strong enough parts, then pursuit of equipment would merely be for proof-of-concept demonstrations and to build understanding – not to produce parts of economic value. It is important to recognize that even with original equipment manufacturer (OEM) machine parameters, it is likely to take considerable time before a new-user is able to achieve optimal material properties due to the continuous learning and improvement nature of individual machines and part geometries. Secondary acceptability criteria includes whether the suspect part(s) fit within the build volume. Specific details concerning part dimensions and machine characteristics are needed to drive cost and production calculations.

If multiple processes and machines are identified as viable for the suspect part(s), then a method is needed to determine which might produce the best value. Between different processes and different machine vendors within each process, a nominal value may be created by key decision factors. Among the most important data of interest for machine evaluation are build volume, speed, and machine cost.

We may quantify machine information, not only for comparison, but also for production and financial implications. Taking the three dimensions of the build envelope as Cartesian coordinate axis dimensions (d_x), (d_y), and (d_z), we may compute the total build volume (v_{build}) by equation (2). Consistent with industry specifications, the author recommends using units of millimeters in calculations.

$$v_{build} = d_x * d_y * d_z \qquad (2)$$

Concerning the machine speed, a distinction needs to be made regarding conventions. Some process classifications, including powder bed fusion, binder jetting, and vat photopolymerization measure speed by distance covered per unit time (i.e., millimeters per second), while others (material extrusion, material jetting, and direct energy deposition) measure speed according to the weight of material deposited per unit time (i.e., kilograms per hour). As such, a direct comparison cannot be made between powder bed and deposition machine. Thus, conversions need to be conducted on a volumetric basis.

If we take a powder bed system under consideration, we may approximate a maximum volumetric scan rate (S_{vol}) based on the machine's scan speed (S_{scan}), focus diameter (d_f), and layer thickness (t_{layer}) by equation (3). Figure 3.5 provides a visual for comprehension. Notice that these speeds reported are maximum approximations as different materials require different energy densities for fusion. This is also why manufacturer-reported deposition rates do not include information regarding weight of what material. Recognizing that density is equivalent to mass per unit volume, we may easily convert between volumetric rates and deposition rates (S_{dep}) by use of material density (ρ), per equation (4).

$$S_{vol} = S_{scan} * d_f * t_{layer} \tag{3}$$
$$S_{dep} = S_{vol} * \rho \tag{4}$$

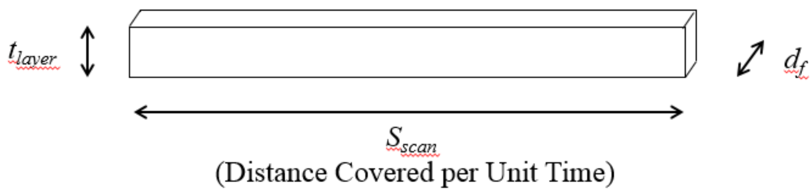

Figure 3.5 Depiction of volumetric scan rate

Finally, we account for the cost of the machinery. However, this value should not consist solely of the initial machine cost reported on a price tag ($c_{initial}$), but rather inclusive of all fixed costs associated with the machine. Variable costs will be dependent on amount of use and are not accounted for here. In this model, machinery fixed costs include costs for the initial machine, complementary machines, overhead, labor, utilities, transportation, installation, software, maintenance, spare parts, and safety certification. Many of these values can be estimated through consultation with machine vendors and industry users. Note that for initial machine comparisons, the additional costs may be assumed to be equal and negligible, allowing the total machine cost to equal the initial machine cost. The extended fixed costs are incorporated here for quantification purposes in the eventual assessment between using additive manufacturing or conventional manufacturing to provide more accurate results.

Complementary machine costs (c_{comp}) refer to all additional machinery required for operation of the AM machine tool, dependent on process. In powder bed systems, for example, this value may include the price of a powder sieving unit, filter wash station, vacuum, inert gas, chiller, or kiln. Mathematically, this can be represented as the sum of all complementary machine costs (i) for a given number of sources (n), as shown in equation (5).

$$c_{comp}(i) = \sum_{i=1}^{n} c_{comp,i} \tag{5}$$

While many approaches are used to quantify overhead, in this case, overhead may be regarded as the annual cost of facility space for all equipment and activities associated with the machine ($c_{facility}$) in addition to a coverage percentage placed corporately on the machine value ($c_{coverage}$), with respect to the machine cost ($c_{initial}$) (Banker et al., 1992). Equations (6) and (7) provide the resulting summation for overhead cost (c_{OH}).

$$c_{coverage} = (c_{initial} + c_{comp}) * \%_{coverage} \tag{6}$$
$$c_{OH} = c_{facility} + c_{coverage} \tag{7}$$

Similarly, other cost values, such as labor (c_{labor}), software licensing ($c_{software}$), maintenance (c_{maint}), spare parts (c_{spares}), utilities ($c_{utilities}$), and safety certification (c_{safety}) may be held as annually reoccurring costs. The remaining two fixed costs, transportation (c_{trans}) and installation ($c_{install}$), are one-time sunk costs for the machine. Thus, we can identify the sunk costs ($c_{m,\,sunk}$) and the annual costs ($c_{m,\,annual}$) for the machine with equations (8) and (9).

$$c_{m,sunk} = c_{initial} + c_{comp} + c_{trans} + c_{install} \tag{8}$$
$$\begin{aligned} c_{m,annual} = {} & c_{OH} + c_{labor} + c_{software} + c_{maint} \\ & + c_{spares} + c_{utilities} + c_{safety} \end{aligned} \tag{9}$$

Due to the presence of sunk and annual fixed costs, a valuable approach to determining the total machine cost ($c_{machine}$) is to take the present value of all sunk and annual cash flows for the life cycle of the machine. The lifespan of a current AM machine (l) is used for depreciation and cash flow purposes; the author suggests designating this value as five years due to the rapid progression in machine technologies. For discounting purposes, all annual costs should be discounted at the weighted average cost of capital (WACC), denoted (w_j %) for all annual costs (j). As a result, the present value total machine costing model can be expressed by equation (10). Figure 3.6 is provided to visualize the cash flows over the machine lifespan. Note that this formulation assumes that there is no salvage value obtainable for selling the machine at its end of life. If that is to be incorporated, it must also be factored into the present value conversion.

$$c_{machine} = c_{m,sunk} + c_{m,annual}\,(P/A, w_j\,\%\,, l) \tag{10}$$

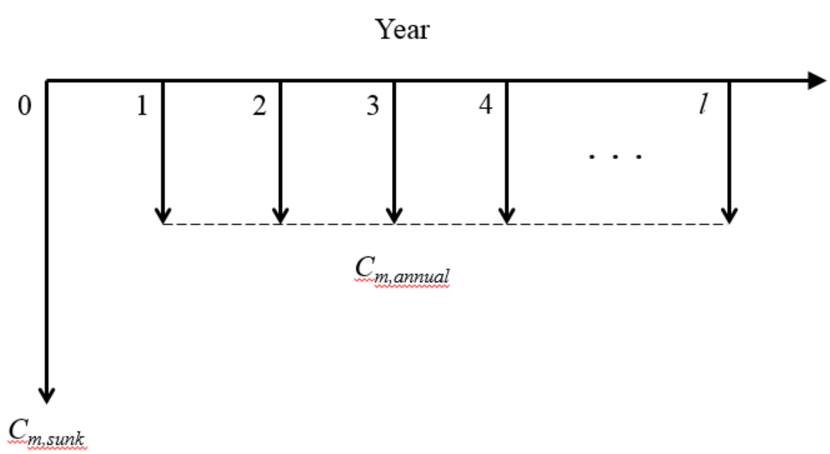

Figure 3.6 Expected cost cash flows for (l) years at a (w%) discount rate

Now that we have a representative value for machine costs, we may calculate indicator values for comparisons. The cost per unit of build volume (c_{vol}) may be determined by equation (11). Similarly, equation (12) indicates the cost per deposition rate (c_{dep}); be aware that this value will likely be high considering the total machine cost is being divided by a small value corresponding to the kilogram deposition rate. Finally, a dimensionless indicator value (I) may be determined by weighting costs, speeds, and machine resolution (r_m) with user defined weights (w_k) for each of the criteria (k). A weighting system is used to allow users to indicate preferences in machine characteristics. Note that this dimensionless value is not restricted to these indicators; a variable ($c_{indicator}$) is provided in equation (13) to represent any additional metrics.

$$c_{vol} = {}^{c_{machine}}/_{v_{build}} \tag{11}$$

$$c_{dep} = {}^{c_{machine}}/_{s_{dep}} \tag{12}$$

$$\begin{aligned} I = \ & w_{cost} * c_{machine} + w_{volume} * v_{build} + w_{speed} * S_{dep} \\ & + w_{resolution} * r_m + \sum_{k=1}^{n} \left(w_k * c_{indicator,k} \right) \end{aligned} \tag{13}$$

Determining Current Capabilities

In evaluation of the business case for investing in additive manufacturing, it is important to understand production information and associated costs of the identified suspect part(s), as made by conventional manufacturing. These values are much more difficult to estimate mathematically, as multiple approaches can be taken to produce the same part. Thus, suspect part costs must be determined individually by either analysis of the company’s specific processes, eliciting a quotation from a fabrication shop, or using online quotation estimates. The main information required is the unit cost (incorporating all factors indicated in equation 10), the unit value (sales price) or markup percentage, annual production requirement, and unit lead time.

Determining Additive Potential

Build Quantification

Once we have determined the suspect machine and part specifications, we may investigate the AM machine tool’s ability to meet or alleviate annual demand. The first step in this process is to determine how many parts will be in each build. The literature confirms common theory that being able to incorporate as many parts as possible in a single build reduces the average part cost as more parts can be created and costs spread across them accordingly (Thomas and Gilbert, 2014). For this reason, many packing density algorithms have been proposed (Ikonen et al., n/a; Wodziak et al., 1994). While these algorithms may produce the maximum number of parts achievable in a given build, alternative methods are easier for estimation basis. Further support for the use of the simpler method proposed lies in the degree of risk which a machine operator is willing to take. If the machine consistently runs without issue, the algorithms become relevant; however, many operators leave space between parts primarily for heat management purposes. Note that it is acceptable to use a part packing algorithm to determine the number of parts in a build with the broader methodology proposed.

In the simplified method proposed, we begin by determining how many parts can fit across the area of the build plate (p_{layer}). To accommodate ambient space for thermal control, we increase the cross-sectional area of the bounding box by a factor (b_{space}); this value is used in calculations as a percentage, but it could simply relate the expanded area of the cross-section. Determination of the number of parts capable on a single build layer can be found by equation (14). This value must be rounded down to the nearest integer to represent only producing whole parts.

$$p_{layer} = \frac{d_x * d_y}{a_{cs} * \left(1 + b_{space}\right)} \tag{14}$$

Then, we must acknowledge the amount of support material required. While difficult to determine mathematically, the CAD slicing software mentioned previously (i.e., Materialise Magics), that generates the support material, can subsequently provide the amount of support material required to produce the part (s_{part}). Then, we must consider the method of part removal. In many cases, the part may be removed at the part and build plate interface; however, it is common in metal processes to add a height of support material (s_{plate}) between the part and build plate so that it may be cut off with a saw rather than more expensive methods. In many cases, this height is slightly more than the width of the saw blade to allow for deviation during cutoff.

Additionally, in some processes (powder bed fusion in particular), where there is ambient material to the parts to provide structure and heat dissipation, parts may be 'nested' or stacked on top of each other along the z-axis to take advantage of available space remaining in the build volume, as depicted in Figure 3.7. With part nesting, although some processes (such as electron beam melting) do not require a solid basis on which to build, most methods require a height of support material between part layers (s_{nest}). Note that this support material is not placed on top of the highest part layer. The number of nested part rows (n_{rows}) may be calculated via the build volume and bounding box height, as shown in equation (15). This value must be rounded down to the nearest integer. Thus, the total number of parts in a given build (p_{build}) may be calculated according to equation (16). In each case, supports must be removed after building by either chemical or mechanical means. Taking these support types into consideration, we must determine the volume of solidified material needed for parts and supports in each build (v_{mat}); the formula for which is shown in equation (17) below. Note that support material is not fully dense, thus it needs to be reduced by a fill percentage (s_{fill}).

$$n_{rows} = \frac{d_z - (h_{box} + s_{plate})}{h_{box} + s_{nest}} + 1 \tag{15}$$

$$p_{build} = p_{layer} * n_{rows} \tag{16}$$

$$\begin{aligned} v_{mat} = \; & p_{layer} * [v_{part} + (s_{plate} * a_{cs} * s_{fill})] + \\ & p_{layer} * [v_{part} + (s_{nest} * a_{cs} * s_{fill})] * (n_{rows} - 1) \end{aligned} \tag{17}$$

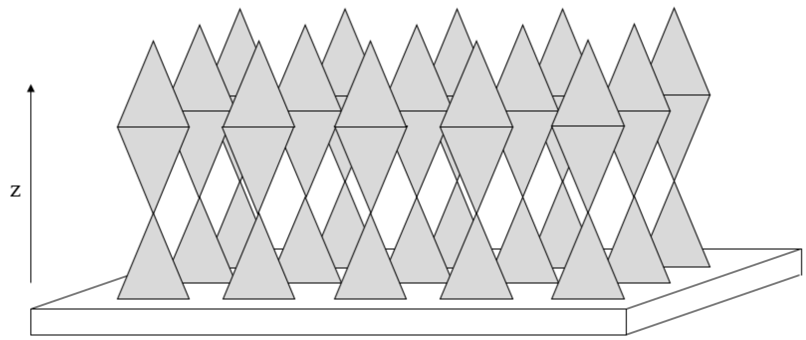

Figure 3.7 Part nesting on a build plate

Note that, for builds involving a single layer of parts, 'n_{rows}' is equal to one. Equation (17) may be rearranged to provide a simpler formula shown in equation (18). For assistance in visualizing what each parameter represents, Figure 3.8 was created.

$$v_{mat} = p_{layer} * [v_{part} * n_{rows} + a_{cs} * s_{fill} * (s_{plate} + s_{nest} * n_{rows} - s_{nest})] \tag{18}$$

Although part mixing is not focused on in this report, the author wishes to mention the capability of this process to handle it. In cases of mixed part types on the same build, bounding box procedures would be performed for all suspect parts, and the same process followed. The difference enters upon calculating the number of parts. One approach is to assume equal number of each part are produced. In this case, the bounding box could become an aggregate, encompassing all parts. The drawback to this, however, is that it increases the potential for unfilled build space. A second approach would be to assign weighting values or ratios to the part array. Packing algorithms are useful in these scenarios, as part mixing creates mathematical complexity. Once the number of parts and associated volumes are determined, all further calculations may performed as normal.

If we consider the total build height, we may proceed in determining the time required to make the parts. Total production time for a build ($t_{production}$), also known as lead time, can be divided into three phases: pre-build, build, and post-build times (Alexander et al., 1998).

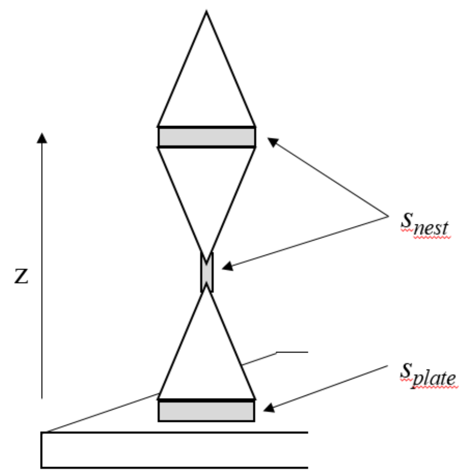

Figure 3.8 Depictions of support material

Pre-build ($t_{build,pre}$) refers to all processes before depositing the first layer of material; this includes file, material, and machine preparation. The build phase (t_{build}) refers to the actual machine operation from deposition of the first layer to build completion. Finally, post-build ($t_{build,post}$) refers to the time between build completion and the parts becoming ready for application; this includes part removal, machine cleaning, and any post-processing required. Due to the highly variable and user-dependent nature of the pre- and post-build phases, they are only mentioned here and represented in equation (19) below. Only build time will be focused on in this report.

$$t_{production} = t_{build,pre} + t_{build} + t_{build,post} \tag{19}$$

Many approaches to calculating build time are provided in the literature (Amini, 2014; Baumers et al., 2016; Campbell et al., 2008). Two leading methods are to calculate build time based on deposition rate or volume. The deposition rate approach relies primarily on two factors, deposition rate and the weight of the part. Similarly, volumetric approaches use the overall build volume, the machine tool's volumetric rate, and the volume of material composing the build parts. While both approaches are capable, a volumetric approach is taken in this method to provide easier future calculations for powder bed fusion, binder jetting, and vat photopolymerization techniques.

It is common for parts to be divided into cubic units called voxels for volumetric approaches, but the mathematics driving these analyses can be intensive for a simple business estimate, as they require individual parts to be broken down into component cubes and summed across three axes (Baumers et al., 2012). In this proposal, build time is driven directly by the volumetric speed of the machine and the material volume. As a reminder, because machine scan speeds reported are often maximum or nominal values, actual speeds will vary according to the energy density required to fuse the material. Thus, the total scan time (t_{scan}) may be determined by the volume of material and volumetric machine speed as shown in equation (20). The 3,600 factor converts the value from seconds to hours. Note that this model does not consider the potential for areas of a solid part to avoid direct disposure (as according to hatch size), time compensation for part geometry (such as speed variance around corners), different parameters for borders, nor the ability to scan a powder bed layer multiple times. This model solely considers the part volume and machine scan rate.

$$t_{scan} = \frac{v_{mat}}{S_{vol}} \; / \; 3600 \tag{20}$$

Using the build plate area and total build height (h_{build}), as determined by equation (21), we may additionally calculate the overall build volume (b_{vol}) via equation (22). Note that 'b_{vol}" is less than or equal to the machine tool's available build envelope 'v_{build}'. This value will be important for future calculations.

$$h_{build} = s_{plate} + h_{box} + (n_{rows} - 1) * (h_{box} + s_{nest}) \tag{21}$$

$$b_{vol} = d_x * d_y * h_{build} \tag{22}$$

The build height can help us determine the number of layers required for the build. Equation (23) determines the number of layers (n_{layers}) by use of the machine tool's layer thickness setting (t_{layer}). This layer thickness should be the same value used in equation (3) for determining the machine's volumetric scan speed.

$$n_{layers} = \frac{h_{build}}{t_{layer}} \tag{23}$$

We must now quantify the additional time elements that comprise build time with two additional variables, layer recoat time and layer cooling time. These variables are necessary to account for certain process factors. Powder bed fusion, binder jetting, and vat photopolymerization all contain filled build areas of material, iteratively deposited layer-by-layer. As such, in the powder bed and binder jetting cases, there is additional time required for each material layer to be spread. While seemingly small in value from a per layer perspective, this additional time becomes significant in the context of an entire build, especially for annual production estimates.

Layer recoat time (t_{recoat}) is necessary for powder bed fusion and binder jetting processes as each subsequent layer of material is iteratively, and mechanically, spread across the build plate. Layer cooling time (t_{cool}) is a brief period after the machine tool energizes the material, but before recoating, in which the fused material is allowed to cool slightly. Without cooling, the material may trap additional material during recoat, potentially leading to porosities. Additionally, localized areas may become over-energized by thermal cycles, leading to part warping. The author acknowledges that in many systems there are sub-processes present regarding these variables, such as optical scans; these are ignored in this model, being incorporated into recoating time. It is also assumed that the machine recoats the build plate effectively with every pass. Equation (24) provides the resulting formula for build time. If needed, convert all time values into units of hours by using the 3,600 factor.

$$t_{build} = t_{scan} + n_{layers} * \frac{(t_{recoat} + t_{cool})}{3600} \tag{24}$$

Now that we have the number of parts on a given build and the time required to complete the build, we may assess production volumes.

Production Volumes

To evaluate production quantities achievable, we must first determine the amount of time available for the machine tool to operate. As operational policies are dependent upon corporate strategy, a formulaic model is required. Beginning with 365 days in a given Gregorian calendar year, we subtract time elements in accordance with corporate policy. Specifically, these institutional factors include days off for weekends ($t_{weekends}$), holidays ($t_{holidays}$), operator vacation ($t_{vacation}$), and maintenance down-time ($t_{maintenance}$). Therefore, we can determine the number of operational days available (t_{days}) by equation (25). It is assumed that the machine will be dedicated to a particular material for all production, with parameters known, such that material change-over and parameter development times may be ignored.

$$t_{days} = 365 - t_{weekends} - t_{holidays} - t_{vacation} - t_{maintenance} \tag{25}$$

Thus, we can find the AM machine tool's annual time capacity ($t_{capacity}$) by equation (26). The value is multiplied by a factor of twenty-four to convert the number of days into hours, consistent with build time units.

$$t_{capacity} = t_{days} * 24 \tag{26}$$

This idealized capacity should not be directly used to calculate part production quantities due to asset utilization amounts. Although the machine may be available for '$t_{capacity}$' hours, it is not likely to be utilized to 100% capacity. Thus, we introduce a utilization rate variable (u). Finally, we may find the maximum number of builds possible in a given year (n_{builds}), and subsequently the maximum number of annual part production (n_{parts}), by equations (27) and (28). Remember to round the number of builds down to the nearest integer value.

$$n_{builds} = \frac{t_{capacity} * u}{t_{production}} \tag{27}$$

$$n_{parts} = n_{builds} * p_{build} \quad (28)$$

As a reminder, this is an idealized case. In reality, other factors reduce the number of annual part production. Primary reductions include time to understand the machine and develop adequate parameters ($t_{develop}$), scrap parts, and time for any material change-overs (t_{change}). Scrap parts may be represented as a percentage of annual production (r_{scrap}). Thus, a more accurate representation would be to adjust equations (26) and (28) to equations (29) and (30), respectively. Because the parameter development time only occurs in the first year, it is ignored in future calculations for this report.

$$t_{capacity} = 24 * \left(t_{days} - t_{develop} - t_{change}\right) \quad (29)$$

$$n_{parts} = n_{builds} * p_{build} * \left(1 - r_{scrap}\right) \quad (30)$$

Production Costs

Once we know production capabilities, we can estimate costs incurred beyond fixed costs. Among these include energy use and material costs. While few cost estimation models exist in the literature for energy use, largely due to high variation levels in consumption, we may estimate it to more closely represent accurate investment costs (Baumers et al., 2016; Gutowski et al., 2006). Machine power ($e_{machine}$) refers to the relatively constant energy consumption rate necessary to operate the machine; this is essentially the machine's energy consumption rate when idle. Deposition power ($e_{deposition}$) refers to the amount of energy needed to fuse a given volume of the material. Thus, the total energy consumption for a build (e_{build}) may be represented by equation (31) below.

$$e_{build} = e_{machine} * t_{production} + e_{deposition} * t_{scan} \quad (31)$$

This value, combined with the cost of energy at the user's location (e_{cost}), can determine the approximate energy cost per build ($c_{e,build}$), shown in equation (32). Equation (33), resultantly, reports the annual energy cost for part production ($c_{e,production}$).

$$c_{e,build} = e_{build} * e_{cost} \quad (32)$$

$$c_{e,production} = c_{e,build} * n_{builds} \quad (33)$$

Next, annual material costs must be determined. Because powder bed fusion, binder jetting, and vat photopolymerization processes all require a full build volume of material, we may compute the amount of material to fill a build volume by equation (35), where ($\rho_{apparent}$) is the apparent density of the material, expressed as a percentage of wrought density (ρ). Apparent density is used, rather than wrought density, because most AM materials exhibit differential part and material densities. This may be attributable to porosities in the material and a packing factor. It is important to recognize that this material volume encompasses the entire build volume, of both part and ambient material, according to (b_{vol}) from equation 22; note that this is not the total machine build volume capacity. Ambient material is typically collected and recycled. Remember to ensure density is in units of kilograms. This should not be used for deposition methods; equation (34) indicates how to calculate the mass of material (m_{mat}) needed for deposition processes. Therefore, the annual cost of material can be calculated by equation (36), where (c_{mat}) corresponds to the material cost per unit of mass. Note that it is recommended to have a small quantity of extra material, regardless of method.

Material deposition processes

$$m_{mat} = v_{mat} * \rho_{apparent} * \rho * n_{builds} \tag{34}$$

Powder bed processes

$$m_{mat} = b_{vol} * \rho_{apparent} * \rho * n_{builds} \tag{35}$$

$$c_{mat,production} = m_{mat} * c_{mat} \tag{36}$$

Additionally, we may determine the material cost per part ($c_{mat,part}$) as shown in equation (37).

$$c_{mat,part} = \frac{c_{mat,production}}{n_{parts}} \tag{37}$$

Total Costs and Requirements

Therefore, we can begin estimating total costs for investment in the AM machine tool. Referring back to equation (10), we may use equation (38) to identify the total fixed costs for the machine (C_{fixed}). Similarly, equation (39) uses the determined energy and material costs to provide expected variable costs ($C_{variable}$) for the lifespan of the machine (l). Because variable costs may incur in the future, their estimated values are discounted to present values, as done previously with fixed costs in equation (10).

$$C_{fixed} = c_{machine} \tag{38}$$

$$C_{variable} = \left(c_{e,production} + c_{mat,production}\right)\left(P/A, w_j\%, l\right) \tag{39}$$

Thus, the combination of the two produces the present value of the estimated total investment cost (C_{total}) for the lifespan of the investment, shown in equation (40).

$$C_{total} = C_{fixed} + C_{variable} \tag{40}$$

If we wish to examine cost drivers, it is useful to convert the total investment cost into an annual amount (C_{annual}), as shown in equation (41), in reflection of annual production rates.

$$C_{annual} = C_{total}\left(A/P, w_j\%, l\right) \tag{41}$$

This is useful in case we wish to view any component metrics from a cost impact perspective. We may similarly compare metrics on a per hour basis. For example, we may determine the total annual cost per part (C_{part}) with equation (42), or the cost per operating hour (C_{hour}) by equation (43). One may notice that the cost per hour increases as the utilization rate decreases.

$$C_{part} = \frac{C_{annual}}{n_{parts}} \tag{42}$$

$$C_{hour} = \frac{C_{annual}}{t_{capacity} * u} \tag{43}$$

Valuation Considerations

Now that we understand the cost structure, we must understand the monetary value of the parts to identify the profit differential. Profit is used to understand the payback structure of the investment. The total value placed on an AM part, however, may be different than the general market price of a conventionally manufactured part, due to external value addition, thus it should not be used a direct indicator for manufacturing comparison. Rather, the case should be compared from an overall investment return perspective, such that both cases are observed over an equivalent scale of production. The use of additive manufacturing processes can enable cost savings and value addition external to part production, such as through supply chain simplification, sustainability improvements, and machinery replacement; ignorance of those factors may indicate incorrect conclusions. Further, different entities can place different value amounts on the same part, potentially yielding investment in AM worthwhile for one, but insufficient for the other. Thus, we must identify potential areas of value; these may additionally be referred to as opportunity costs of manufacturing methods.

Value addition and cost savings directly attributable to the AM production part include sustainability, weight reduction, and benefits of increased complexity. An important driver for AM sustainability is the reduction in material waste. Because AM can often use less or recycle excess material easily, waste amounts are significantly less than many conventional processes. For AM, material waste stems from supports and any post-processing waste. Comparatively, conventional processes, especially milling operations, typically generate more waste as material must be removed to create the part structure, or excess material is supplied to ensure a complete cavity fill. For direct energy deposition, waste reduction and manufacturing value generation may also include the ability to repair parts. This methodology has capabilities to fill and repair cracked metal dies and castings, providing significant cost savings for replacement and disposal. Weight reduction may increase part value dependent upon the use of the product. For example, making aerospace parts lighter weight can reduce fuel costs, thus generating value (Campbell et al., 2012). Finally, the ability to add complexity for free can provide part capabilities that are either expensive to manufacture conventionally or generate intrinsic value.

Additionally, since AM can often replace multiple steps in the conventional manufacturing process, one may financially benefit from machine substitution. Replacing multiple machines with an AM machine can decrease the amount of required space, resulting in costs savings from overhead and asset reassignment. As such, value generation may be achieved through machine proximity to customers. Reducing lead times, especially for spare parts or replacement parts, can have a significant impact on a company's operations. An example includes a cargo ship with a broken mechanical unit. Combined with the cost of delaying cargo shipment, the replacement piece for the broken unit could be costly to fabricate and transport to the ship. By having a machine on deck that can produce a replacement part on-site, the company could significantly reduce lead time and resulting costs. Further savings may be obtained through network externalities such as customization value and savings through the supply chain, such as procurement and transportation costs.

Finally, we must determine the generic, base market value (or selling price) of the part, independent of manufacturing method. The market value may be used as the product price for conventional manufacturing, and the basis of value for an AM part; external value addition is to be placed in addition to the base market price. Determining the market price may be done in one of two ways, markup and market value. Markup, or profit margin, refers to a corporately defined percentage above part cost at which the part is sold. Market value is the price a buyer in the marketplace would pay for the good, regardless of manufacturing method. Market value may be determined by comparing competitive price listings available, using the unit value of the current production method, or by obtaining a quote from a conventional fabrication shop. For a fair evaluation, market value (V_{market}) should be used.

Thus, we may represent estimated AM part value as a culmination of all identified factors. As many variables can be difficult to quantify upon initial inspection, approximations may be made. Equation (44) provides the formulation for estimated part value (V_{part}), where value add is reflected by a sum of additional value sources (a_{value}), inclusive of value accumulation from sustainability, weight reduction, complexity, machine substitution, reduced lead times, customization, transportation, procurement, and other sources (i), all on a present value per part basis. Note that values may be negative, indicating the switch to AM reduces value for that particular field.

$$V_{part} = V_{market} + \sum_{i=1}^{s} a_{value,i} \tag{44}$$

We may now calculate the unit profit () as the difference between part value and part cost with equation (45). This value is used to determine the breakeven point and annual income expectations for the life of the investment.

$$P_{part} = V_{part} - C_{part} \tag{45}$$

Decision Analysis

Initial Comparison Procedures

With this information determined, we may begin to compare additive versus conventional manufacturing capabilities in part production. For fair comparison, conventional manufacturing costs must be reported in a likewise manner to the additive manufacturing cost structure. This is important to ensure that CM part costs include overhead, material wastes, and all associated factors. Note that if the difference between AM and CM processes for a given factor were accounted for in the AM value (such as savings from asset reassignment), they should not be counted again.

Beyond part comparison, it may help to determine performance indicators such as break-even point and throughput rate. A system's breakeven point occurs when the cumulative profit obtained equals the investment cost. This is estimated as a ratio of total fixed costs to the unit's contribution margin (value less unit variable cost). Meanwhile, throughput provides a production metric regarding how much output the system can produce over a given interval of time. In this case, throughput is calculated in terms of production, not the annual availability. Equations (46) and (47) provide the formulas for breakeven point in units (B_{units}) and throughput rate (T), respectively.

$$B_{units} = \frac{C_{fixed}}{V_{part} - \left({}^{C_{variable}}\!/_{n_{parts}} \right)} \tag{46}$$

$$T = \frac{p_{build}}{t_{production}} \tag{47}$$

Breakeven point may alternatively be viewed by the number of years required to reach that point (B_{time}), as determined by equation (48). If this value is larger than the lifespan of the project, then the investment should not be pursued.

$$B_{time} = \frac{B_{units}}{n_{parts}} \tag{48}$$

Additional metrics companies often refer to for investment decisions include return-on-investment (ROI) and the investment's present worth, both of which relate to the projected cash flows over the lifespan of the investment. Many corporations maintain a minimum ROI for investment (a minimum rate of return), which may indicate whether or not the investment should be pursued. Alternatively, the present worth (PW) of the investment indicates if the project is expected to be profitable or not; if the PW is positive, then it indicates profitability, if not, then the project should not be pursued. Note that it is assumed in this case that AM is being investigated as a substitution for CM production. There are some cases in which the investment may not be profitable, but AM could be less costly than expanding CM capabilities.

Sensitivity Analysis

Once all valuations are performed, sensitivity analysis should be conducted to reflect variations in approximations and provide a more accurate depiction of investment outcome. For this, select parameters are adjusted to determine how they affect the overall business case. Key parameter variations suggested include changing the number of parts per build (p_{build}), utilization rates (u), production time ($t_{production}$), build volume (v_{build}), deposition rate (S_{dep}), annual capacity ($t_{capacity}$), energy consumption rates (e_{build}), material cost (c_{mat}), and the market value (V_{market}). Analysis of these parameters can provide a better understanding of operational cost structure, and indicate where improvements need to be made for AM to become viable for investment.

Final Decision Criteria

If it is determined that AM may be a worthy investment, it is recommended that the viewer perform a real-world test to validate estimates. This may be done by submitting one or more suspect parts to a contracted site for fabrication, tracking parameter values throughout. Then, the evaluation process should be repeated using the proven data to determine a more realistic investment outcome. If the results still indicate adoption, then the investment should be pursued.

Case Study Application

To demonstrate this process for both reference and analysis, a case study is provided. The case study will be performed for the suspect part indicated in Figure 3.9. Additive manufacturing equipment used for this analysis is an EOSINT M 270 powder bed fusion machine tool. Information about the machine tool and material was obtained online from EOS's website and the AM community (EOS, 2017; DMLS Technology, 2017; Lay3rs, 2017; MatWeb, 2017). Parameters and assumptions used in calculations are provided in Chapter Four. Comparison judgement will be based data taken from Baumers et al., 2012, in which the same suspect part was evaluated by a different methodology. Results are provided and discussed in Chapter Four.

Figure 3.9 Turbine wheel of dimensions 54 x 54 x 28 mm, volume 20,618 mm^3, 2012 (Baumers et al.)

Chapter Four

RESULTS AND DISCUSSION

Parameters and Assumptions

Parameters used in this case study were drawn from an EOSINT M 270 informational sheet DMLS Technologies 2017, MatWeb 2017, Lay3rs 2017, and Baumers et al. 2012. Provided parameters are shown in Tables 4.1 – 4.3. Additional parameters were estimated, as according to Table 4.4. Assumptions taken in the approach to fulfillment of the case study are listed in Table 4.5.

Case Study Results

The process introduced in Chapter Three were followed with the parameters indicated above. Results of the calculations involved are provided below in Tables 4.6 – 4.13. The total unit cost was found to be $171.68, a 3.71% difference from Baumers et al.'s 2012 estimate for the same part. The total investment cost over the five-year lifespan, in terms of present value, was $3,241,710. Fixed costs accounted for 63.1% of this total. Further, material costs accounted for 36.7% of annual costs, while only 0.19% was attributable to energy consumption. Labor costs accounted for only 15.6% of the total annual cost. Annual production yielded 5,238 units, at a 1.4 parts per hour throughput rate. Build time accounted for 88.8% of production time, with 63.3% attributable to exposure, or scan time. The breakeven point occurs at 11,920 units, or 2.28 years for a $400 part value.

Sensitivity Analysis

Sensitivity analysis was performed on part value, scan speed, material cost, parts per build, utilization rate, machine capacity, and overhead percentages to evaluate their effects on either annual costs, cost per part, breakeven years, or annual production quantities. All adjustments were done from the base values used or determined in the case study. Part value was adjusted from -50 – 100% change in value, in increments of 10%. All other values were adjusted from -100% - 50% change in value, also in 10% increments. Figures 4.1 – 4.9 provide the resulting relationships.

Table 4.1 EOSINT M 270 Machine Data, 2017 (DMLS Technologies; Lay3rs)

Description	Variable	Value
x-axis Length	d_x (mm)	250
y-axis Length	d_y (mm)	250
z-axis Length	d_z (mm)	215
Scan Speed	S_scan (mm/s)	7,000
Focus Diameter	d_f (mm)	0.1
Layer Thickness	t_layer (mm)	0.02
Initial Machine Cost	c_initial ($)	$464,400
Total Machine Cost	Total Price ($)	$702,000
Machine Resolution	r_m (mm)	0.1

Table 4.2 Suspect part data, turbine wheel, 2012 (Baumers et al.)

Description	Variable	Value
x Dimension	x (mm)	54
y Dimension	y (mm)	54
z Dimension	z (mm)	28
Part Volume	v_part (mm3)	20,618

Table 4.3 Material information and comparative part cost, 2012 (Baumers et al.) and 2017 (MatWeb)

Description	Variable	Value
Material Density	ρ (g/mm3)	0.0077
Material Cost	c_mat ($/kg)	$97.72
Literature Part Cost	Baumers's part cost ($)	$165.54

Table 4.4 Assumed values for case study

Description	Variable	Value
Coverage Percentage	%_coverage	20%
Facility Cost	c_facility ($)	$75,000
Labor Cost	c_labor ($)	$140,000
Software Cost	c_software ($)	$1,300
Maintenance Cost	c_maint ($)	$5,000

Table 4.4 Continued

Description	Variable	Value
Spare Parts Cost	c_spares ($)	$5,000
Utilities Cost	c_utilities ($)	$5,000
Safety Cost	c_safety ($)	$500
Transportation Cost	c_trans ($)	$1,000
Installation Cost	c_install ($)	$500
WACC	w%	12%
Investment Length	l (years)	5
Cost Weight	w_cost (%)	40%
Volume Weight	w_volume (%)	30%
Speed Weight	w_speed (%)	20%
Resolution Weight	w_resolution (%)	10%
Criteria Weight	w_k (%)	0%
Boundary Spacing	b_space (%)	5%
Plate Support Height	s_plate (mm)	3
Nest Support Height	s_nest (mm)	5
Support Fill Per.	s_fill (%)	20%
Pre-build Time	t_build,pre (hr)	4
Post-build Time	t_build,post (hr)	8
Recoat Time	t_recoat (s)	5
Cooling Time	t_cool (s)	5
Weekend Days	t_weekends (days)	104
Holiday Days	t_holidays (days)	10
Vacation Days	t_vacation (days)	10
Maintenance Days	t_maintenance (days)	10
Utilization Rate	u (%)	70%
Development Time	t_develop (days)	0
Change-out Days	t_change (days)	0
Scrap Rate	r_scrap (%)	3%
Machine Energy	e_machine (W)	5,500
Deposition Energy	e_deposition (W)	200
Energy Cost	e_cost ($/Whr)	8E-05
Apparent Density	ρ_apparent (%)	99.5%
Part Value	V_part ($)	$400

Table 4.5 General assumptions made for case study

Assumptions
1.0 Euro = 1.08 USD
1.0 Pound = 1.24 USD
All machine parameters are consistent
Bounding box is a cylinder
Full build envelope capacity available
Labor includes 1 engineer & 1 technician
Laser power constant at max. capacity
Machine can run overnight
Machine does not stop
Machine parameters known
Maximum machine power consumption
No material change-overs
No pre-exposure or duplicate exposures
Parts are nested in the build

Table 4.6 Cylindrical bounding box dimensions

Description	Variable	Value
Diameter	diameter (mm)	54
Height	h_box (mm)	28
Cross-Sectional Area	a_cs (mm2)	2,290
Box Volume	v_box (mm3)	64,126

Table 4.7 Machine costs and characteristics

Description	Variable	Value
Build Envelope Vol.	v_build (mm3)	13,437,500
Volumetric Dep. Rate	S_vol (mm3/s)	14
Mass Dep. Rate	S_dep (kg/s)	0.0001
Comp. Equipment	c_comp ($)	$237,600
Machine Coverage	c_coverage ($)	$140,400
Total Overhead	c_OH ($)	$215,400
Sunk Costs	c_m,sunk ($)	$703,500
Annual Costs	c_m,annual ($)	$372,200
Total Mach. Costs	c_machine ($)	$2,045,198
Cost per Volume	c_vol ($/mm3)	$0.15

Table 4.8 Build times and characteristics

Description	Variable	Value
Parts per Layer	p_layer	25
Rows per Build	n_rows	6
Parts per Build	p_build	150
Vol. of Material	v_mat (mm3)	3,413,331
Production Time	t_production (hrs)	106.95
Build Time	t_build (hrs)	94.95
Scan Time	t_scan (hrs)	67.72
Height of Build	h_build (mm)	196
Build Volume	b_vol (mm3)	12,250,000
Build Layers	n_layers	9,800

Table 4.9 Annual production capabilities

Description	Variable	Value
Operational Days	t_days	231
Machine Capacity	t_capacity (hrs)	5,544
Annual Builds	n_builds	36
Annual Parts	n_parts	5,238

Table 4.10 Machine energy consumption information

Description	Variable	Value
Energy per Build	e_build (Whr)	601,754
Energy Cost per Build	c_e,build ($)	$48.35
Annual Energy Costs	c_e,production ($)	$1,741

Table 4.11 Material cost information

Description	Variable	Value
Annual Material Mass	m_mat (kg)	3,379
Annual Material Cost	c_mat,production ($)	$330,184
Part Material Cost	c_mat,part ($)	$63.04

Table 4.12 Total investment cost structure

Description	Variable	Value
Total Fixed Costs (PV)	C_fixed ($)	$2,045,198
Total Variable Costs (PV)	C_variable ($)	$1,196,512
Total Cost (PV)	C_total ($)	$3,241,710
Total Annual Cost	C_annual ($)	$899,282

Table 4.13 Decision metrics for evaluation criteria

Description	Variable	Value
Part Cost	C_part ($)	$171.68
Hourly Cost	C_hour ($)	$231.73
Part Profit	P_part ($)	$228.32
Breakeven Units	B_units	11,920
Breakeven Time	B_time (years)	2.28
Throughput Rate	T (parts/hr)	1.40

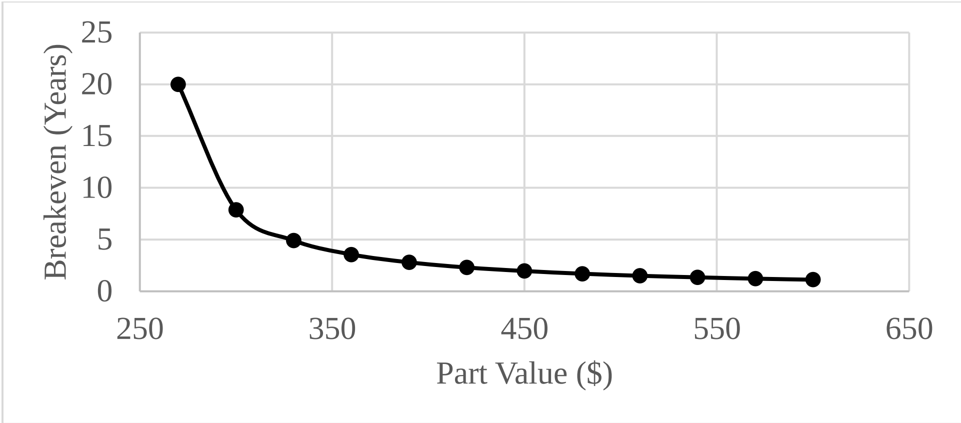

Figure 4.1 Part value's impact on breakeven (years)

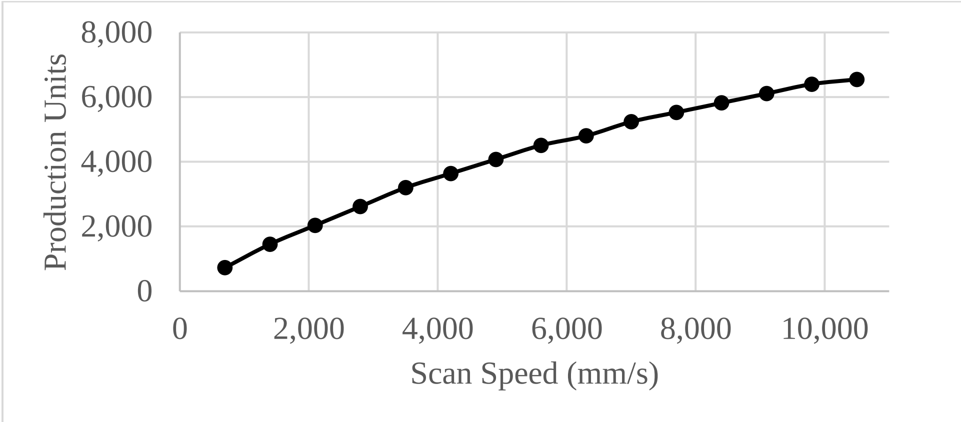

Figure 4.2 Scan speed's impact on annual production quantities

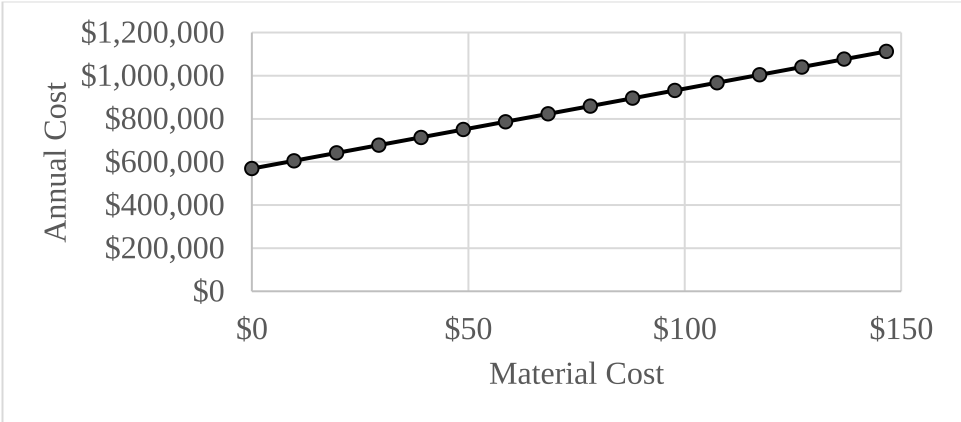

Figure 4.3 Material cost's impact on annual cost

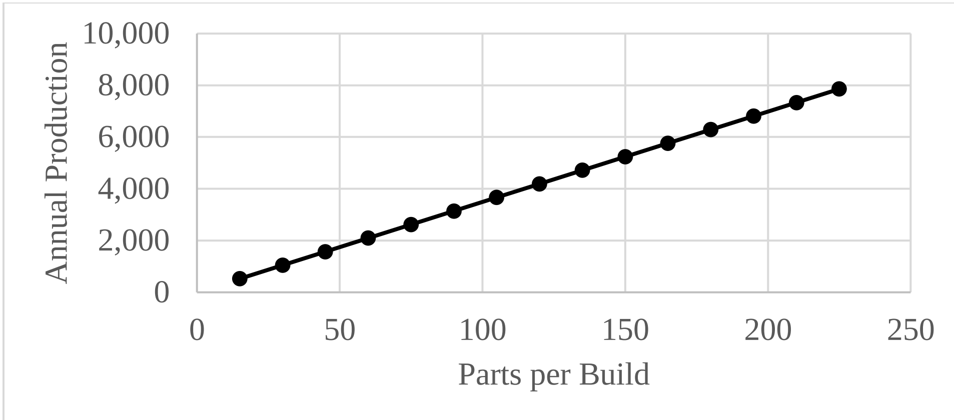

Figure 4.4 Number of parts per build impact on annual production quantities

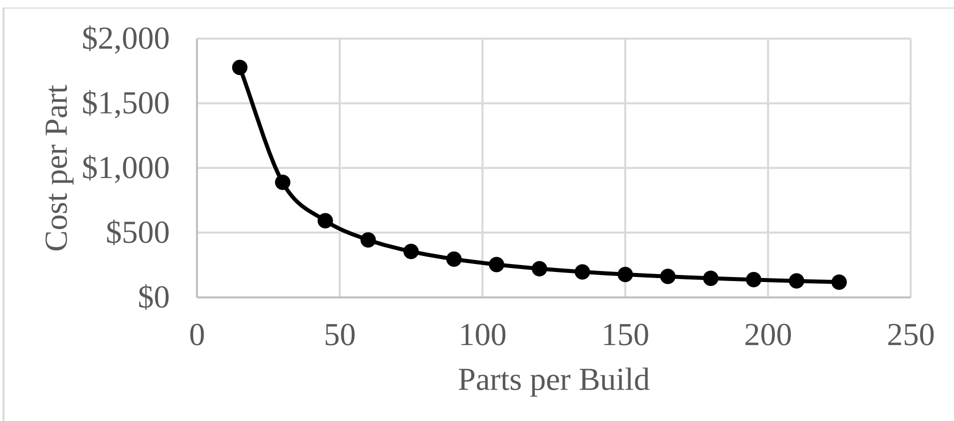

Figure 4.5 Number of parts per build impact on cost per part

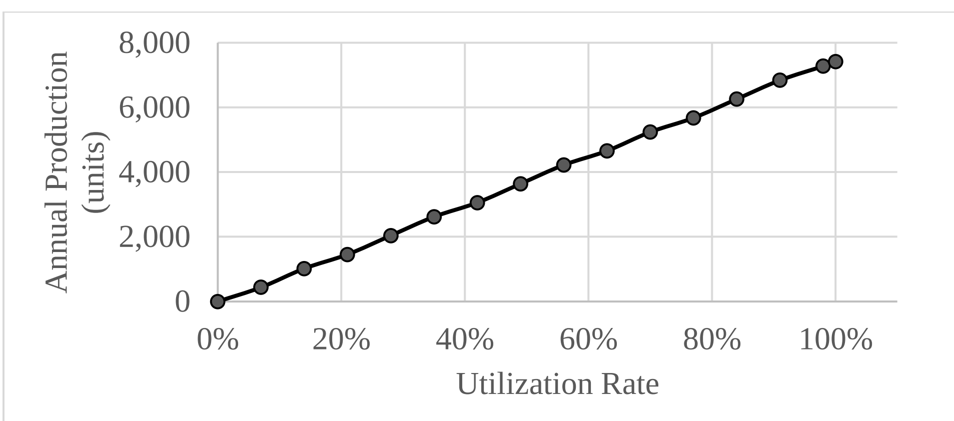

Figure 4.6 Utilization rate's impact on annual production quantities

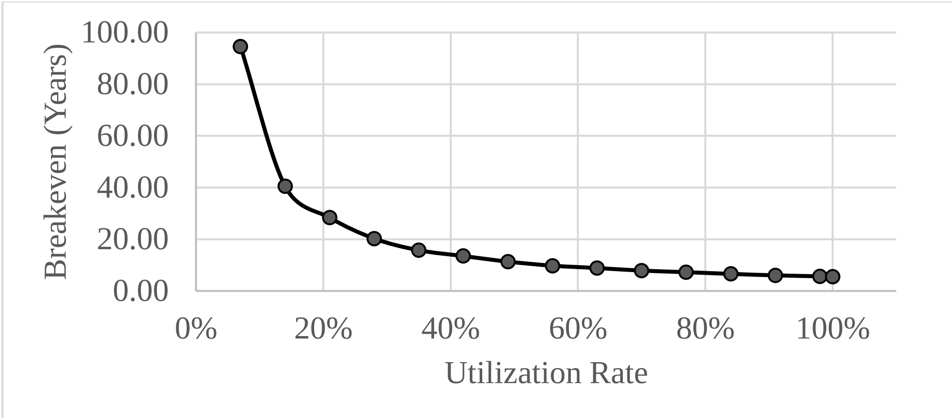

Figure 4.7 Utilization rate's impact on breakeven (years)

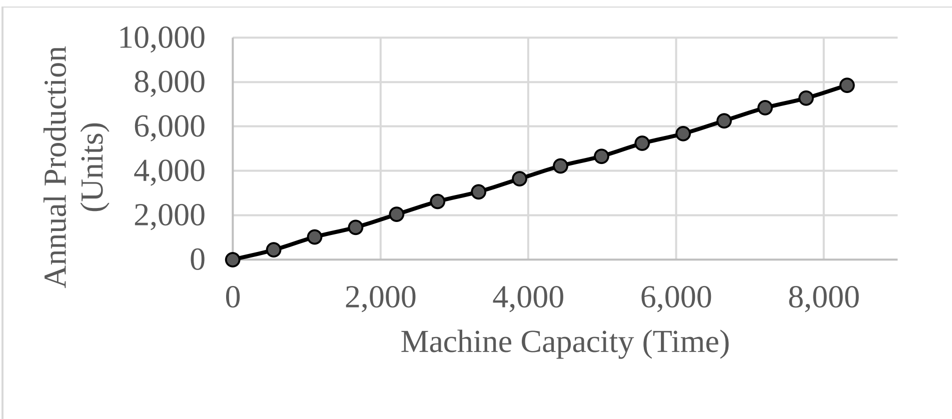

Figure 4.8 Machine availability capacity's impact on annual production quantities

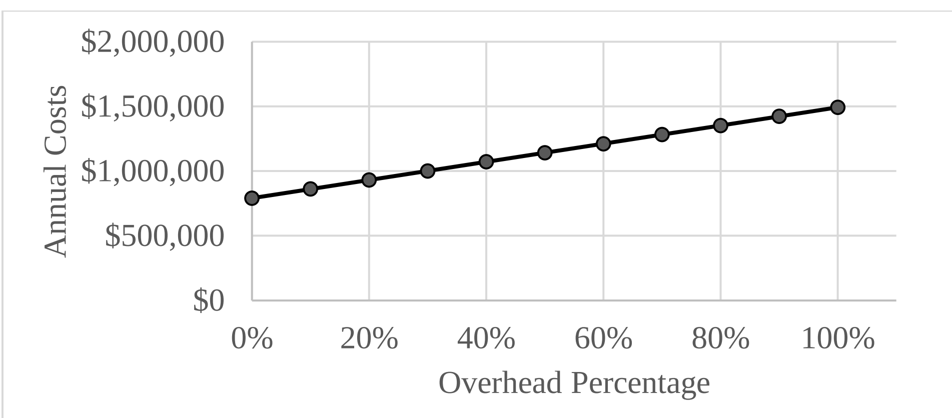

Figure 4.9 Overhead percentage's impact on annual costs

Discussion

Results indicate that the EOSINT M 270 should be pursued for investment to produce the turbine wheel. This decision was reached in consideration of the project's positive net present value and its ability to reach the breakeven point before the end of investment life. With this in mind, sensitivity analysis indicates that for the investment to break even at the end of project life (five years in the case), the system must either produce 4,014 units annually or value each part at $306.53. This means that as long as the system annually produces at least 4,014 units on average, or as long as the determined AM part value is above $306.53, with all else constant, AM production remains a viable option.

Additional observations made from sensitivity analysis include the importance of machine capacity, utilization, material cost, and scan speed. As shown in Figures 4.2, 4.4 – 4.8, being able to produce more parts per build can dramatically impact output and resulting cash flows. Whether this be done through larger build volumes, increasing scan speeds, or increasing the time in use through capacity or utilization rates, improvement in any can create a significant output increase or cost decrease. As noted, material costs account for 36.7% of annual costs. A $19.54 reduction in material price (20%) can lead to $66,037 in annual cost savings.

Noted sources of error in the process include factors of estimation and misrepresentation. As several variables in this process are contextually dependent, they become difficult to model and estimate. As more of these factors are introduced, complexity and resulting error increase. An example demonstrated in the case occurred in estimating energy consumption, as it is reported elsewhere in the literature that energy cost is more considerable towards overall costs than 0.19% identified. As such, this reflects the need to review generated results to re-evaluate assumptions and estimations.

No conventionally manufactured price was found for the turbine wheel to compare manufacturing methods. While it may be possible for a given company to estimate or locate conventional manufacturing costs, the part price will vary between entities due to differing manufacturing methods, requirements, and economies of scale. However, the part cost determined by the proposed method yielded a 3.71% difference compared to the Baumers estimate, indicating the model's acceptable cost estimation capabilities.

Chapter Five

CONCLUSION AND RECOMMENDATIONS

Through this thesis proposal, a procedure for evaluating additive manufacturing technologies for production purposes has been introduced in the form of nine identification and quantification steps. Once a part has been identified as suspect for AM production, part geometry and required physical properties can help determine an appropriate AM technology and machine for inspection. With part and machine information, annual production capabilities and cost structure may be estimated for the life of the equipment. Further investigation of part market price and external value addition, such as complexity, sustainability, and supply chain simplification, can provide a relative part value to assess the expected return on investment. This part value, however, is subjective to the case of the individual entity, and thus may not be directly quantified. To reflect the influence of likely changes, or to indicate what components need to change, sensitivity analysis may be conducted, providing a more realistic expectation of investment outcomes. This procedure is useful as a simple process by which one may evaluate whether or not production of a given part should be performed by additive manufacturing as opposed to conventional methods.

As a demonstration of method, a case study popular in literature was reproduced, with a 3.71% difference in resulting cost estimation per part, reflecting the viability of the proposed method. Decision criteria for acceptance was driven by the operational metrics of annual production and throughput rate, as well as financial metrics of breakeven point, annual cost, and present worth. For the turbine wheel and EOSINT M 270 system presented, the model indicated that additive manufacturing is a viable production method for the part. By performing sensitivity analysis of variables, machine costs and material costs were identified as key drivers of the AM cost structure. Similarly, it was found that improvements in scanning or deposition speeds, machine capacity, and utilization rates can increase production efficiency, providing greater annual yield and increasing return. As such, continued development is needed to improve not only process control, but also to progress the technology for industry commercialization. Until market competition and innovation drive cost reductions, corporate investors will remain hesitant to adopt additive manufacturing as a complementary manufacturing process. As shown by the production volume of the case study, current beneficiaries include those requiring small-to-mid series production and complex geometries that increase part value.

Future development for the process is suggested to include modeling expansion, refinement, and real-world validation. As seen in the case study, much of the ending result was dependent upon context estimations. The ability to better identify and model these values can improve the reliance and accuracy of the process, leading to more accurate information for decision-making. The individual equation models should also be compared to real-world data to validate their structure, limitations, and accuracy levels. This may be done by performing a real-world trial of a case study and comparing demonstrated values to calculated estimates. It is expected that energy consumption will have the largest area of refinement within costing. Other model developments include incorporating post-processing and the risk structure of the investment. While the model does include scrap and utilization rates, it does not account for other risks such as issues with material supply. The final area of process development would be to improve part value modeling to better encompass and identify the various sources of value addition associated with additive manufacturing.

Finally, as this paper identifies a simple approach to evaluating the viability of additive manufacturing for part production, the process may be developed into a software tool for quick investigation. With the equations provided as a backbone, a user-friendly graphical user interface (GUI) could allow direct import of a part's CAD file for analysis. The software would use the CAD model as an input to determine part dimensions and volume; future iterations could also include topology optimization suggestions. Once the user supplies material property criteria, the software could suggest material types and associated commercially available equipment. For full evaluation, the software may be integrated with a company's database system to automatically pull accurate, real-time values for conventional manufacturing costs and several value generation fields. With the CAD information and corporate data, the system can follow the calculations presented herein to return additive manufacturing viability information and sensitivity analysis through KPI graphical displays. In this way, the part evaluation process could be reduced to a simple file upload and viability output. Expansion could allow for multiple part types, from which a production plan could be created.

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